Gordon Institute
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Transforming Piotroski's (binary) F-score into a real one

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Abstract

Since the 1960s, accounting researchers have attempted to assess the benefit of historical financial statements to capital market investors (Bunting & Barnard, 2015) by developing an indeterminate number of predictive signals designed to “beat the market”.

One such stock screen, the Piotroski F-score (Piotroski, 2000), attempted to reverse the trend of increasingly complicated predictive algorithms by applying a simple binary calculation method to nine signals extracted from widely accessible historical accounting data. While Piotroski found the F-score to be effective in separating winners from losers, subsequent studies delivered mixed results.

This research sought to interrogate the relevance of the F-score’s nine signals on the JSE and to assess a revised calculation methodology, based on a ranked scale of companies. The results of the research were also used to assess the ongoing relevance of accounting-based fundamental analysis in light of the challenges posed by behavioural finance research and technological advances.

The results show that six of the F-score’s nine signals were found to be relevant to the JSE and the ranked scale calculation approach was successful in separating winners from losers. Analysis of the F-score’s predictive ability over time showed that accounting-based fundamental analysis remains relevant in the context of the JSE.

Keywords

Fundamental analysis, anomalies, stock screen, predictive signals

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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Transforming Piotroski's (binary) F-score into a real one

1.2 Research Problem

The broadest classification of investment strategies is arguably between passive and active investing. The passive investor will buy into an index fund and enjoy the same returns, suffer the same losses and be exposed to the same levels of risk as the fund. Active investors seek to outperform indices buy selecting and trading individual stocks, or assembled portfolios, in line with their own philosophies and approaches. One approach applied by the active investor is the use of accounting data to identify stocks that may outperform the market.

The Piotroski F-score is a stock screen that relies solely on accounting data to classify a company's financial performance, as either good or bad, on nine different signals. While simple in design, the F-score's binary nature may also be its biggest flaw. If performance can only be classified as being either good or bad, one may be eliminating the potential benefits of a scaled ranking that places companies along a spectrum from the best performing to the worst.

1.3 Background

In the novel Pudd'nhead Wilson, Mark Twain outlines his view on investment risk with the aphorism "October: This is one of the peculiarly dangerous months to speculate in stocks. The others are July, January, September, April, November, May, March, June, December, August and February." ("Pudd'nhead Wilson Quotes", n.d.).

The desire to achieve the highest possible return, or at least to outperform average market returns, lies at the core of many ever-evolving investment strategies. For some, intuition and experience act as mitigators, however enhanced data processing and computing technology has seen the development of numerous stock screens which aim to guide investment decisions.

The belief that investors are somehow able to “beat the market” raises a direct challenge to what was once considered conventional wisdom by many academics and market observers. Fama (1970) sought to dispel the notion that superior returns are possible through the Efficient Market Hypothesis (EMH).

The EMH relies strongly on the argument that the market considers all available information in the public domain and is therefore able to set accurate prices. However, subsequent research has shown that certain investment strategies and styles that made use of publically available information were able to outperform market returns over the long term. These findings posed a direct challenge to the EMH and investors have dedicated much effort to developing algorithmic stock screens by making use of such research (Muller & Ward, 2013).

One such stock screen, the Piotroski F-score (Piotroski, 2000), has attracted wide interest ever since the Chicago accounting professor Joseph Piotroski devised the measure in 2000. The F-score applies fundamental analysis to historical accounting data to determine a set of nine signals that can be applied in assembling a portfolio of value stocks, or stocks with a high book-to-market ratio. Stocks with high F-scores are classified as “winners” and their returns are expected to outperform the universe of value stocks while low F-scores indicate possible “losers”.

Of importance is the fact that a stock’s F-score is derived from historical accounting data that is widely available in the public domain. It is therefore the kind of data that, according to the EMH, should be factored into a stock’s price as it becomes publicly available. A further advantage of the F-score is that it is relatively easy to calculate by considering information on the following variables: gross margin, net income, return on assets, asset turnover, operating cash flow, debt to assets, the current ratio, the change in shares outstanding and the quality of earnings (Muller & Ward, 2013).

The results of each calculation are expressed in binary terms as either a one for a good signal or a zero in the case of a bad signal. It assumes that the result of each signal carries an equal weighting unlike, for example, the Z-Score (Altman, 1968) that applies different weightings to five financial ratios in an attempt to predict the likelihood of corporate bankruptcy.

Analysis for the period 1976 to 1996 showed that an investor who bought winners and shorted losers from the universe of value stocks on the New York Stock Exchange would have generated an average annual return of 23% (Piotroski, 2000) and therefore outperformed average market returns. However subsequent research delivered mixed results.

Woodley, Jones and Reburn (2011) found that the F-Score did not distinguish winners from losers in the 12 years following Piotroski's sample period and concluded that a good rule had gone bad. Bunting and Barnard (2016) however found this conclusion to be somewhat premature and vulnerable to contradictory evidence from lesser-examined market partitions.

Van der Merwe (2012, p. i) found no conclusive evidence that the F-score was able to screen stocks with significantly higher returns from a portfolio of value stocks selected from the Johannesburg Stock Exchange (JSE) for the period 2000-2011. Van der Merwe offers possible explanations for his findings, with one being that the F-score's effectiveness may have been impacted by the JSE's overall strong and persistent bull market during the sample period as well as the possible impact of the JSE's relatively small value stock universe.

Research has also attempted to test modified versions of the F-score. An important variation was confirmed by Piotroski (2004) who found that the screen could be applied to portfolios of growth stocks (low book-to-market ratios) and not only value stocks as initially believed. These findings were confirmed by a number of researchers including Zhou and Tice (2011), Mohr (2012) and Pullen (2013).

With conflicting findings on the effectiveness of the F-Score, further research is required to test if historical accounting data remains relevant in identifying stocks that deliver superior returns. This is particularly important in an environment where technological advancement has facilitated a more rapid and wider distribution of data, and improved methods of analysis.

The increasing amount of behavioural finance research also poses a challenge to a purely rational approach. Complex human decision-making processes, and their impact on share prices, can never be captured by a relatively simple stock screen that relies purely on historical accounting data.

A further consideration from previous research findings is whether all of the F-score's nine signals are relevant across different markets and if a modification to its simplistic binary calculation methodology would be effective in separating winners from losers.

1.4 Purpose of the Research

The purpose of the research was to expand on prior work conducted in the field of accounting-based fundamental analysis by assessing the relevance of the F-score's nine signals within the context of the JSE. The research also attempted to assess the application of a modified F-score calculation methodology to establish if it would be successful in separating winners from losers. The research consists of two major parts.

The first part of the research examined the relevance of the F-score's nine signals in identifying winners from losers on the JSE. The scope of the research included shares listed on the JSE for the period 31 December 2004 to 31 October 2017. Each signal's predictive capability was separately assessed using Piotroski's (2000) binary calculation methodology. Signals that were shown to be relevant for the chosen population were combined into a revised JSE-relevant F-score that also made us of the original binary approach.

The decision not to apply an initial value stock screen was informed by the argument on the limitations of the JSE's small value stock universe (Pullen, 2013, p. 5) as well as research indicating that the F-Score could be applied to both value and growth stocks (Piotroski, 2004; Zhou & Tice, 2011; Mohr, 2012).

The second part of the research proceeded to transform the F-score by amending the simplistic binary methodology to achieve a scaled ranking of companies. Only those signals found to be relevant in part one of the research were included in the transformed F-score. An assessment was then conducted on the ability of the revised calculation approach in separating winners from losers on the JSE for the sample period. Finally, an analysis of the results of this research was used to assess the ongoing relevance of accounting-based fundamental analysis on the JSE in light of the challenge posed by behavioural finance research and technological advances.

1.4.1 Academic Rationale for the Research

While researchers have attempted to identify links between accounting variables and stock price returns for many decades, accounting-based fundamental analysis only began to attract substantial academic interest following the work of Ou and Penman (1989), Holthausen and Larcker (1992) and Feltham and Ohlson (1995). This increased focus led to a number of conclusions on a broad range of single accounting variables, and combinations of variables, that could serve as predictors of superior returns.

Subsequent research sought to combine macroeconomic indicators with accounting data as observed in the work by Lev and Thiagarajan (1993) as well as Abarbanell and Bushee (1997). As researchers began devising more complex algorithms, and with the increasing popularity of behavioural finance, Piotroski (2000) sought to reverse the trend with a simple measure that relied solely on nine signals obtained from a company's historical accounting data.

While the F-score has been tested across a number of different periods and on various stock markets, limited research has been performed on variations to its composition and calculation methodology.

This research therefore contributes to the overall body of knowledge on accounting-based fundamental analysis and its general contradiction of the EMH. The research seeks to confirm whether the conclusion reached by Ou and Penman (1989), namely that financial statements capture fundamentals that are not reflected in prices, is still relevant following almost three decades of technological advancement. While the advantages of such technological advancement is applied to a more complex calculation methodology, the context is one where investors have wider and more timely access to information and analysis tools than when the F-score was first developed. The possibility that technological advances may eventually lead to a situation where all fundamental information is captured and reflected in prices certainly deserves more consideration.

This research also highlights the tension between rational approaches and the more complex concept of investor psychology (Hirshleifer, 2001) with a view to ascertaining the ongoing relevance of the former within the context of the JSE.

1.4.2 Business Rationale for the Research

Many fundamental analysis techniques apply accounting data to determine an intrinsic stock value. Well known examples include the discounted cash flow method (Ward & Price, 2015, p. 117) and the application of price-to-earnings multiples. This determined value is then compared with current market prices in order to identify mispriced securities for investment purposes (Kothari, 2001).

Piotroski (2000) applied an initial value stock screen using a stock's price-to-book ratio. Therefore the original F-score did consider market prices in order to define the population. However, by eliminating the value stock screen, this research constructs portfolios without considering market prices and explores the value of historical accounting data to the investor in the absence of any knowledge of market prices.

Additional motivation for this research stems from technological advances that have made it possible to perform more complicated analyses with greater ease than when the F-score was originally developed. Richardson, Tuna and Wysocki (2010) argue that advances in computing technology may have reduced the likelihood of discovering and exploiting price anomalies as more investors and fund managers have access to sophisticated tools which help to determine fair prices. Investors are also faced with the threat that technology has facilitated a more timely and wider distribution of information which could reduce the possibility of exploiting price anomalies.

With an increasing number of sophisticated and complicated stock screens and investment styles, it is worth investigating the ongoing relevance of a purely rational approach that only applies widely available public information with no consideration for market prices. The benefit of the research to investors includes the findings on which of the F-score's nine signals were proven to be relevant within the context of the JSE and, importantly, which signals were found to be counterproductive.

While the F-score's attractiveness may originally have been bolstered by its simplistic binary nature, such simplicity could possibly be a weakness following fifteen years of technological advancement. This research therefore explores whether an amendment to the F-score methodology would be effective in separating winners from losers.

1.5 Summary of Findings

This research makes important findings with regards to the application of the Piotroski F-score on the JSE. In line with the research questions, the findings are summarised as follows:

1) Not all of the F-score's nine signals were found to be relevant in separating winners from losers on the JSE. Three of the signals were found to have little or no predictive ability while two of the signals were found to be counterproductive in the manner in which Piotroski (2000) applied them.

2) A revised F-score calculation methodology (PiotroskiTrfm), applied only to those signals found to be relevant to the JSE, was successful in separating winners from losers over the sample period. A portfolio consisting of the highest PiotroskiTrfm scores would have delivered an annual return of 22% over the sample period while the lowest scoring PiotroskiTrfm portfolio only generated annual returns of 5.9%.

3) No evidence was presented to suggest a decline in the ability of accounting-based fundamental analysis, as applied by the F-score, to separate winners from losers on the JSE.

This research confirms the assertion made by Abarbanell and Bushee (1997) that investors should not assume the relevance of all of the F-score's nine signals across different markets and time periods. Certain signals may actually be counterproductive and their application may therefore reduce investment returns.

A revised F-score calculation methodology, based on a ranked scale is introduced and tested. It is important to note that this research does not attempt to make a finding on whether the binary methodology delivers superior results to the ranked scale methodology. Instead, the revised calculation methodology is shown to be successful over the sample period with the recommendation that it be further tested and repeatedly compared with the original methodology in different markets and over different time periods.

An important finding is reached regarding the ongoing relevance of accounting-based fundamental research. Despite the opposition to a purely rational approach by behavioural finance research, and the threats posed by technological advances, this research finds that accounting-based fundamental analysis has retained its validity in separating winners from losers on the JSE.

1.6 Outline of Research Report

The research proceeds in chapter two with a literature review outlining the theoretical basis for the application of accounting-based fundamental analysis. A description is provided of the F-score and its nine signals together with a summary of its application in prior research. An outline is provided of the challenges posed to accounting-based fundamental analysis by behavioural finance research as well as technological advances. The literature review concludes with key findings from prior research that raise important questions about possible variations to the F-score's calculation methodology.

Chapter three explains the research questions and hypotheses as derived from the literature review. Chapter four describes the research methodology and design and includes a description of the stock universe and sample as well as data collection methods. In chapter five the results of the research are presented while chapter six contains a discussion and analysis of these results. The research report concludes in chapter seven with the principle findings and suggestions for future research.

2. Literature Review

2.1 Introduction

Fundamental analysis comprises an investment strategy that considers a combination of economic, industry and historical accounting information in order to gain an understanding of a stock's potential future value. More than four decades of research has produced at least 330 individual predictive signals (Green, Hand & Zhang, 2013) and an indeterminate number of combinations designed to "beat the market".

Accounting-based fundamental analysis eliminates many general signals by only focussing on a company's historical accounting data. The practice is underpinned by the premise that accounting constructs have external validity due to their relevance in the determination of stock values (Bunting & Barnard, 2016). In practice, the investor would seek to identify undervalued stocks, based on their fundamentals, in the belief that the market has not yet considered all available accounting information. By only focussing on a company's accounting data, the investor would be applying a purely rational approach to stock pricing – a strategy that is not without criticism.

Technological changes that have improved the timeliness and distribution of information, together with an increasing number of findings in the field of behavioural finance have sought to challenge the ongoing relevance of accounting-based fundamental analysis. Despite criticism of the strategy, research suggests that a purely rational approach is still successful in beating the market and that the results are not achieved by chance, but instead, stem from the mispricing of stocks (Yan & Zheng, 2017).

2.2 Theoretical Basis for the Application of Historical Accounting-based Fundamental Analysis

Bunting and Barnard (2016) explain that, since the 1960s, accounting researchers have attempted to assess the benefit of historical financial statements to capital market investors. The central question underpinning many decades of research has been to determine whether or not accounting data could be used as a predictor of future stock price returns and therefore inform an investment strategy that ignores market and macroeconomic information.

One of the earliest studies on accounting-based fundamental analysis (Ball and Brown, 1968) supported the assumption that capital markets are efficient and unbiased and that asset prices fairly reflect all available information. Based on that assumption, it was accepted that accounting data, when released, would have an impact on stock prices. However, Ball and Brown also argued that the delayed release of financial statements limited their impact as the market would have access to more recent data through the media. Such assertion, if true, would be even more relevant today due to a broader coverage of traditional media networks and the mass adoption of social media.

Research by Fama (1970) supported Ball and Brown's assumption by concluding that markets did generally reflect all available information in asset prices. The exception to what became known as the efficient market model, or efficient market hypothesis (EMH), was where company insiders and specialists had monopolistic access to information. The EMH was defined at three levels, namely strong, semi-strong and weak form market efficiency depending on the type of information and the degree to which such was reflected in prices.

The widely held belief that the EMH was credible seemed to quash the possibility that an investor could "beat the market" over the medium to long term. In line with this assumption, most research in the 1970s and 1980s focussed mainly on short-window even studies (Kothari, 2001). However, expanded studies over longer time periods led many academics to challenge the EMH, including Fama himself, by noting that subsequent research highlighted its shortcomings (Fama, 1991). Frankel and Lee (1998) provided a more direct explanation by stating that the market was a lot slower in adjusting prices to fundamental information than what prior evidence suggested.

The EMH was not alone in being discredited following many years of broad acceptance. Fama and French (1997) provide a criticism of one of the most widely known models of this nature, namely the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965). The CAPM argues in favour of a relationship between average returns and risk, as measured by beta. Fama and French (1997) explain that there is an increasing body of research showing that the CAPM does not provide an adequate description of expected returns. Their earlier research tested a variation of the model known as the Sharpe-Lintner-Black (SLB) CAPM in which they concluded that such a model was not accurate in predicting returns (Fama & French, 1992). In a study conducted on the JSE for the period 31 December 1986 to 31 December 2011 Ward and Muller (2012) found that the use of a single beta CAPM is inappropriate.

Ou and Penman (1989) provided early evidence of a link between descriptors derived from financial statements and future stock returns without any consideration of market data. The study analysed 68 descriptors and reduced the number by only considering those that were statistically significant. A similar analysis, conducted by Holthausen and Larcker (1992), led them to support Ou and Penman's (1989) findings that financial statement items can be combined into a summary measure that would provide an indication of a company's future stock prices. However, as Piotroski (2000) notes, both of the abovementioned studies made use of complex methodologies that relied on a substantial amount of historical data.

In contrast to Ou and Penman (1989), who performed a statistical search to identify possible descriptors, Lev and Thiagarajan (1993) applied theory and expert judgement to select the fundamental signals that were included in their analysis. Their research identified 12 signals comprising mostly accounting data but extended to elements such as labour force sales productivity, order backlog and audit opinion. A further notable difference is that the 12 signals were conditioned to account for three macroeconomic variables, namely the annual change in the rate of inflation, real gross national product and level of business inventories. The research found that the relation between the 12 signals and future returns were considerably strengthened when conditioned on the identified macroeconomic variables.

Various other studies provide valuable insights on the possible relationship between financial statement data and stock returns by making use of a number of different algorithms. However the link between theory and evidence was conclusively provided by Ohlson (1995) and Feltham and Ohlson (1995) by showing how a company's equity value was determined by owner's equity (balance sheet) and earnings (income statement).

Insightful research conducted by Abarbanell and Bushee (1997) re-examined the application of the fundamental signals identified by Lev and Thiagarajan (1993) and found that there was justification to rely on many, but not all, of the signals in assessing future firm performance. Their findings also confirm that changes to variables such as inflation and gross domestic product (GDP) do have an impact on the relationship between the signals and earnings.

The latter finding by Abarbanell and Bushee (1997) is of significance. If changes to macroeconomic variables impact on the application of fundamental signals in the same market, it would indicate that different markets, subject to differing frequencies and degrees of change in such variables, may require their own unique set of signals to achieve optimum results.

2.3 The Piotroski F-score

Within the context of ever expanding research on accounting-based fundamental analysis, and the search for an optimum set of signals, Joseph Piotroski developed a model called the F-score (Piotroski, 2000). Two important hallmarks of the F-score are its intended application to a broad portfolio of high book-to-market firms (value stocks) and its simplistic nature.

2.3.1 Contextual Analysis (value versus growth stocks)

Early research on fundamental analysis involved large samples and included the entire population of firms with available data. In contrast, most analysts and portfolio managers apply a particular valuation technique to a subset of firms with similar characteristics or to those operating in similar sectors (Beneish, Lee & Tarpley, 2001). The application of contextual analysis would therefore, on the face of it, make sense when attempting to compare the accounting information of firms where no adjustment to such information is made to compensate for significantly different operating environments.

Piotroski (2000) adopted a contextual analysis approach by focussing on value stocks (high book-to-market firms) and noted the findings by Fama and French (1992) that such stocks tend to have higher average returns than growth stocks (stocks with low book-to-market ratios). However, the bias towards value stocks is not only based on their superior returns but also on their perceived risk as they are usually firms experiencing financial distress (Chen & Zhang, 1998). Piotroski (2000) argues that, due to the precarious financial position of these firms, their valuation would be largely based on accounting fundamentals such as leverage, liquidity, profitability trends and cash flow. As this information is easily obtained from historical financial statements, value stocks lend themselves to a valuation method purely based on accounting data.

Piotroski (2000) posits that the basis for a successful value stock investment strategy is being able to identify the few firms with strong performance (winners) while avoiding the many who underperform or even fail (losers). The F-score could therefore be used in a hedging strategy by buying winners and shorting losers.

Piotroski (2000) also highlights that, as a group, value stocks tend to be poorly covered by the analyst community with a low level of forecasts and stock recommendations. The assertion links closely to the findings of Turtle and Wang (2017) that high F-score portfolios appear to display the greatest information uncertainty. This raises questions about investor underreaction to information and specifically historical accounting statements. Safdar (2016) provides a possible explanation in his findings that the F-score is more effective in predicting future stock returns in industries where competition is low and where sources of information are therefore limited. This assertion would certainly increase the likelihood of mispricing.

In applying the value stock screen, Piotroski (2000) calculated the book-to-market ratio (BM) of all shares with sufficient data trading on the New York Stock Exchange (NYSE) between 1976 and 1996. The firms were ranked according to their BM ratio and only those within the highest quintile formed part of the sample that was subject to F-score testing. The methodology was repeated annually and the sample would therefore be adjusted to account for changes in financial statement data and the market value of firms. The approach delivered a final sample of 14 043 value stocks across the 21 years.

Analysis for the period 1976 to 1996 showed that an investor who bought winners and shorted losers from the universe of value stocks on the New York Stock Exchange would have generated an average annual return of 23%. However subsequent research delivered mixed results.

Woodley, Jones and Reburn (2011) found that the F-Score did not distinguish winners from losers in the 12 years following Piotroski's sample period and concluded that a good rule had gone bad. However, Bunting and Barnard (2016) assert that this conclusion is somewhat premature and vulnerable to contradictory evidence from lesser-examined market partitions. Their assertion is supported by Geyfman, Wimmer and Rada (2016) who found that the F-score was successful in distinguishing winners from losers amongst large value stocks on the S&P 500 between 2007 and 2014.

Piotroski (2000) did not test the F-score strategy against firms with a low BM (growth stocks) to assess whether the value stock screen was in fact necessary. However subsequent research by Piotroski (2004) identified that the F-score was effective in separating winners from losers across all the segmented book-to-market portfolios. This provided an indication that the contextual analysis approach was not a prerequisite.

Research conducted by Zhou and Tice (2011) provides further important insight in this regard. They found that the F-score strategy was profitable for both high and low BM firms listed on the NYSE over the period 1979 to 2006 and that such profitability depended on the trading strategy applied (long versus short position) as opposed to the value stock screen.

Pullen (2013, p. 39) confirmed that a modified F-score strategy, excluding the value stock screen, yielded returns that were in excess of those of the general market when applied to stocks listed on the JSE over the period 2004-2012. In a study that analysed returns on the Eurozone Equity Market for the period 1999-2010 Mohr (2012) concluded that the F-score could be applied to separate winners from losers in a growth stock universe.

While Ng and Shen (2016) confirmed previous findings on the F-score's effectiveness across all book-to-market portfolios in seven different Pacific-Basin markets, it is interesting to note that their research was extended to include market capitalisation as a form of contextual analysis. In analysing their results it was discovered that the F-score strategy was most effective amongst small cap portfolios where returns exceeded those of value stock portfolios.

It is therefore apparent that, while the F-Score was originally intended for application to a value stock portfolio, there is sufficient evidence to suggest that it can be applied to all stocks, including those with a low BM.

2.3.2 The F-score's Nine Signals

Having reviewed research that dispenses with the need to apply a value stock screen, it is necessary to outline the nine signals that comprise the F-score. The signals are divided into three categories, namely profitability; leverage, liquidity and source of funds; and operating efficiency.

2.3.2.1 Profitability

The profitability component focuses on current profitability and cash flows as indicators of a firm's ability to generate funds through its primary business activities. The four measures that comprise the profitability signal are described in Table 1.

Table 1: F-score profitability signals

Signal	Description	Binary Scoring
Positive Return on Assets (F_ROA)	Net income (before any extraordinary items) divided by average total assets where average total assets represents the average value of total assets for the previous and current financial years.	A positive ROA will result in a score of 1 while a negative ROA will be awarded a zero.
Positive Cash Flow from Operations (F_CFO)	Obtained from the firm's cash flow statement.	A positive CFO receives a score of 1 while a negative CFO means a score of zero.
Change in Return on Assets (F_ΔROA)	Measures whether the ROA has increased or decreased between financial years.	An increase in ROA results in a score of 1 whereas a decrease is awarded a zero.
Accrual Measure (F_ACCRUAL)	Measures whether net income (before extraordinary activities) is less than cash flows from operations. It serves as an indicator of the firm's future ability to generate profits.	If net income (before extraordinary items) is less than cash flow from operations then the score is 1. If net income is more than cash flow from operations then the score will be zero.

F_ROA, F_ΔROA and F_CFO lacked statistical significance (Piotroski, 2000)

2.3.2.2 Leverage, liquidity and source of funds

The measures identify changes in a firm's capital structure as well as its ability to service future debt obligations. The three measures are described in Table 2.

Table 2: F-score capital structure and liquidity signals

Signal	Description	Binary Scoring
Change in leverage (F_ΔLEVER)	The year-on-year change in total long-term debt divided by average total assets.	An increase in the ratio scores a zero while a decrease will score 1.
Change in liquidity (F_ΔLIQUID)	The year-on-year change in the firm's current ratio represented by total current assets divided by total current liabilities.	An increasing current ratio is considered positive and will receive a score of 1 whereas a decreasing current ratio is awarded a zero.
Change in shares outstanding (EQ_OFFER)	An increase in the number of common shares in issue is considered a signal that the firm was unable to generate sufficient internal funds to service future opportunities and obligations.	An increase in the number of common shares in issue will result in a score of zero. No change or a decrease (through share buy-backs) in the number of shares in issue will score 1.

F_ΔLEVER and EQ_OFFER found to have strongest association with future returns (Piotroski, 2000)

It should be noted that the EQ_OFFER signal is subject to very specific conditions relating to companies listed on the JSE insofar as Broad Based Black Economic Empowerment (BBBEE) legislation is concerned. Companies that issued share capital, in an attempt to transform their ownership structure, would be penalised when measured against this signal.

While researchers strongly defend the notion that the issuing of shares is negatively correlated with future stock returns (Daniel & Titman 2006; Daniel & Titman 2016) this is in the context of identifying a distressed company. This argument is problematic as not all companies that issue common stock can automatically be classified as distressed. The issuing of common stock for the purposes of including a strategic partner is such an example.

In the context of the JSE, one could argue that a transformed ownership structure brings both financial and non-financial benefits and may even go so far as to improve corporate sustainability and a company's going concern status. The country's corporate governance code goes much further than a simple encouragement.

A further consideration is highlighted in research conducted by Ward and Muller (2010), which observed the impact on stock prices following a company's announcement of a black economic empowerment deal. By employing an event study methodology, the research finds that companies with a small market capitalisation experience a positive cumulative abnormal return of 10% following the first year of the announcement while stock prices of larger companies reflect a marginally negative cumulative abnormal return.

The cumulative abnormal returns arising from the announcement of BBBEE deals was not taken into account in this study and is noted as an important limitation. However, as outlined above, a more fundamental question to be asked is whether the issuing of common stock for the purposes of legislative compliance and in the interests of achieving national objectives should be treated as a negative signal.

2.3.2.3 Operating efficiency

Operating efficiency measures focus on year-on-year changes to the firm's gross margins and turnover. Piotroski (2000) identifies these measures reflecting key constructs underlying the decomposition of return on assets.

Table 3: F-score operating efficiency signals

Signal	Description	Binary Scoring
Change in gross margin (F_ΔMARGIN)	Year-on-year change in the firm's gross margin. (Gross profit divided by revenue)	An increase in the gross margin is awarded a score of 1 while a decrease results in a zero.
Change in asset turnover (F_ΔTURN)	Year-on-year change in the firm's asset turnover. (Total revenue divided by total average assets)	An increase in the asset turnover ratio is awarded a score of 1 while a decrease results in a zero.

F_ΔTURN found to display a strong association with future returns (Piotroski, 2000)

2.3.2.4 Composite score

Once a score has been calculated for each of the nine measures the individual scores are then aggregated to obtain a firm's overall F-score. The mathematical equation is represented as:

F-score = F_ROA + F_CFO + F_ΔROA + F_ACCRUAL + F_ΔMARGIN + F_ΔTURN + F_ΔLEVER + F_ΔLIQUID + EQ_OFFER

Due to the binary nature of the individual measures, a firm's F-score can only be a positive integer ranging from zero to nine.

Firms are then ranked according to their F-scores and can be divided into a number of portfolios for analysis. For example, Piotroski (2000) grouped firms with an F-Score of eight or nine as high F-Score firms (winners), whereas firms with scores of one and zero were grouped together in the low F-Score category (losers).

After defining the portfolios it is possible to compare stock returns for a defined period and determine whether such returns where higher for companies that had obtained a high F-score.

2.4 Variations in the Application of the F-score

As can be seen in the tables above, all of the F-Score's nine measures can be calculated from information obtained in a firm's historical financial statements. There are however instances where variations may be required. For example, if a firm does not explicitly report gross revenue (for the calculation of F_ΔMARGIN) then the measure could be replaced by considering a firm's operating margin instead (Pullen, 2013, p. 16).

This raises a general question on how differences in accounting reporting standards may impact on the F-score and a further question on the possible impact of the transition from Generally Accepted Accounting Practice (GAAP) to International Financial Reporting Standards (IFRS).

A recent study on the change to fair value accounting for investment property, as opposed to the traditional measurement at cost, was found to have significant impact on selected income statement signals of a real estate development company. However, the research found that changes to balance sheet signals were limited (Elsiefy & ElGammal, 2017).

An important consideration would be around how frequently a firm's F-score is re-calculated during the sample period. Piotroski (2000) calculated each firm's F-score on an annual basis whereas Zhou and Tice (2011) calculated quarterly F-scores and therefore rebalanced their portfolio every three months. Pullen (2013, p. 17) also applied a quarterly rebalancing approach in order to increase the number of data points to improve the F-Score's statistical significance in the South African context. The frequency with which the F-Score is calculated will also influence the trading strategy.

A further possible variation is found in a suggestion by van der Merwe (2012, p. 71) that the F-score's effectiveness may have been impacted by the JSE's overall strong and persistent bull market during the sample period 1998-2011. A closely linked question is whether or not the F-score's predictive ability is impacted by changes to macroeconomic variables such as GDP and inflation following Abarbanell and Bushee's (1997) conclusion that such changes did impact on Lev and Thiagarajan's (1993) 12 fundamental signals.

Further conclusions reached by Abarbanell and Bushee (1997) hold important insights for possible variations to the F-score's nine signals. Based on their findings, it may be possible that some of the nine signals may not be relevant in a particular market or over a particular sample period. It would therefore be useful to test each of the nine signals individually, to first assess their relevance, and to construct a revised F-score comprising only of the identified signals.

A significant variation to the calculation methodology stems from the F-Score's simplicity. Pullen (2013, p. 17) argues that there is a risk of losing potentially important financial data when information is converted into a binary format. This view appears to make sense as a firm that improved its gross margin by 1% year-on-year would receive the same score for the F_ΔMARGIN measure as a firm whose gross margin increased by 100% in the same period. With only two possible options (zero or one) for the nine measures, the model is limited to 512 possible states in the score.

Two variations have been identified for further focus in this research. The first variation of interest is a possible exclusion of some of the F-score's nine signals should they prove not to be relevant in the context of the JSE and the chosen sample period. The second variation concerns the F-score's binary calculation methodology and the design of a new scaled ranking calculation in attempt to test whether such a variation would be effective in separating winners from losers.

2.5 Threats to Accounting-based Fundamental Analysis

The first source of opposition to accounting-based fundamental research that is explored stems from the field of behavioural finance where research has found links between complex human decision making processes and stock pricing. The central question to fundamental analysts is whether a purely rational approach remains relevant when such is unable to capture the impact of human behaviour and decision making.

The second challenge to accounting-based fundamental research emanates from the basic theory upon which the practice is based – namely that the market has not yet considered all fundamental information in the setting of prices and that prices will adjust accordingly as the information is incorporated.

The theory allows practitioners to identify price anomalies based on historical data and to exploit such over the period of market price adjustments. Of course, this would imply that investors and the market at large do not misinterpret accounting information. However, as Lewellen (2010) explains, increased research has served to shed light on the misinterpretation that can lead to price anomalies

Richardson, Tuna and Wysocki (2010) serve to warn investors and academics by explaining that technological advancement, and its benefits to the processing, interpretation and dissemination of information, may pose a threat to the original theory. The risk to the practitioner is that technological advances may have led to prices already reflecting all fundamental information and that price anomalies are a result of other factors. In such a case, the investor would be making incorrect assumptions on future prices if the assumptions were purely based on historical accounting data.

The two threats introduced above are now discussed in greater detail.

2.5.1 Behavioural Finance

In the same manner that fundamental analysis challenged popular and entrenched models, research into the field of behavioural finance has attempted to debunk the notion that stock prices are simply a function of a set of accounting or macroeconomic signals. Marks (2011, p. 1) voices his opinion bluntly by stating that “investing can’t be reduced to an algorithm and turned over to a computer”.

Drawing on the work of Tversky and Kahneman, De Bondt and Thaler (1985) published important findings on how human behaviour and specifically the overreaction to unexpected and dramatic news events impacted on stock prices. The effects of overreaction were observed up to five years following portfolio formation and could therefore not be classified as short-term mispricing. Following these findings, an increasing amount of research would serve to popularise the field of behavioural finance and question the role that fundamentals played in the determination of stock prices. Hirshleifer (2001) criticised the relevance of purely rational approaches to pricing and suggested that these should fall within the broader field of investor psychology.

The apparent friction between fundamental analysis and behavioural finance is not relevant for the purposes of this research. However, what is important, is that both fields ask critical questions on the link between information and stock pricing.

Fundamental analysis primarily explores the timeframe, and degree to which, the market has included all relevant information in determining prices, whereas behavioural finance explores how such information is interpreted and processed. Therefore, while both fields strongly oppose the EMH and CAPM, they do not necessarily stand in opposition to each other in establishing a link between information and the pricing of stocks. The tension lies in the juxtaposition of rational algorithms and seemingly irrational human behaviour.

Daniel, Hirshleifer and Subrahmanyam (1998) developed a theory based on overconfidence and showed how confidence levels may vary as a result of self-attribution bias. Their theory, which implies that investors overreact to private information and underreact to public information, was further explored by Daniel and Hirshleifer (2015) to explain why investors who process the same public information may hold different views.

Research by Li, Guo and Park (2017) suggests that the causal relationship between investor sentiment and stock returns can be explained by concepts such as loss aversion and herding behaviour. Information that contradicts investor sentiment is hypothesised to cause cognitive dissonance (Antoniou, Doukas & Subrahmanyam, 2013) and may explain mispricing during periods of optimism or pessimism.

The practical application of behavioural finance research can be found in one of the most widely used investment strategies, namely momentum. Jegadeesh and Titman (1993) found that stocks with high returns over the prior twelve months were likely to continue yielding abnormal returns in the first year after portfolio formation. These findings formed the basis for subsequent research that linked the momentum strategy to behavioural models (Jegadeesh & Titman, 2001). A link between investor sentiment and the momentum strategy was also reported by Viljoen (2017, p. i) following research conducted on the largest 160 stocks listed on the JSE over a 27 year period. Viljoen's findings showed that a conventional momentum strategy was most profitable following non-pessimistic periods of investor sentiment.

This research attempts to explore whether a relatively simple stock screen remains relevant in light of a greater understanding of more complex and intangible processes of human decision making and how such may impact on prices. While the definition of complexity is subjective, one plus one will always equal two in the case of accounting-based fundamental analysis whereas behavioural finance researchers suggest that this may not always be true for the human decision making process.

2.5.2 Technological Advancement

The threat posed to fundamental analysis by technological advancement, and its impact on the wider and more timeous distribution of information, makes an important link to the EMH. If influences on pricing from non-rational sources, such as human behaviour, were ignored then ongoing technological advances may support a state in which the EMH could increasingly be proven to be true. However, this scenario is unlikely in an age where media consumers have also been given the opportunity to act as information providers through mediums such as social media.

The increasing adoption of social media has led researchers to question its impact and relevance on stock pricing. While Yu, Duan and Cao (2013) find that social media appears to have a stronger relationship with stock prices than conventional media they caution that it is the interrelatedness of the two that is more important.

A further study on the relationship of social media and stock prices sought to examine the role of user-generated opinions from a popular investment focussed social media platform, Seeking Alpha (Chen, De, Hu & Wang, 2014). The research finds that the frequency of negative words contained in both articles and user comments on the platform do have a relationship with stock returns over the following three months.

The authors provide two possible reasons for this, namely that the platform provides users with value-relevant information that has not yet been factored into pricing or that views expressed on the site cause naïve investor reactions. While the findings attempt to argue that it is the former, one has to consider the degree to which social media has aided in the application of the non-rational approaches described by behavioural finance researchers.

This theme was indeed explored by Nguyen, Shirai and Velcin (2015) whose research constructed a stock price prediction model using the sentiment from social media. While the authors acknowledge that researchers are grappling with how to use social media opinions in prediction models, they argue that the key to resolving this involves a better understanding of what topics are discussed in social media and how people generally feel about those topics.

There appears to be a convention by finance researchers to study social media's interaction with stock prices as a short-term event study, thereby reinforcing the view that fundamentals will ensure correct pricing over the long term. However, if the widespread adoption and increased use of social media continues it may increase the number of significant mispricing events to the point where a correction by fundamentals will be near impossible.

One important source of information, namely academic research, appears also to have benefited from the broader distribution brought about by technology. Insightful research by McLean and Pontiff (2016) observes the link between in-sample returns, post-sample returns and post-publication returns among a large sample of predictors. Their research finds that academic research does draw attention to characteristics and that characteristic portfolios reflect increases in variance, turnover and dollar volume post-publication.

If it is found that more investors are rapidly responding to findings contained in fundamental analysis research then the value of its practical application would increasingly be limited to its pre-publication period. Peavy and Saffran (2010) explain this argument more succinctly when stating that "successful investment techniques that are not kept secret will sow the seeds of their own demise, at least in the long run".

2.6 Summary

The literature review has sought to provide an overview of the theoretical basis for the application of historical accounting-based fundamental analysis by outlining important developments in the field. A detailed description of the Piotroski F-score included recent findings on the screen's applicability to value and growth stocks as well as a description of the nine signals that comprise the overall score.

Selected research findings provide insight on variables and variations that may have an impact on the F-Score’s predictive ability. These insights serve to inform the research questions.

Threats to accounting-based fundamental analysis, in the form of behavioural finance research findings as well as technological advances, were highlighted in the context of establishing the ongoing relevance of a purely rational approach.

3. Research Questions and Hypotheses

The following research questions stem from prior research on the application of the F-score, its possible variations, as well as the general question on the continued relevance of accounting-based fundamental analysis.

3.1 Research Question 1:

Conclusions reached by Abarbanell and Bushee (1997) indicate that it may be possible that some of the F-score's signals are not relevant in a particular market or over a particular sample period. Therefore the first research question is:

Q1) Are all of the F-score's nine signals relevant in separating winners from losers on the JSE?

The null hypothesis, H_o:
Not all of the F-score's nine signals are relevant in separating winners from losers on the JSE.

The alternate hypothesis, H1:
All of the F-score's nine signals are relevant in separating winners from losers on the JSE.

3.2 Research Question 2:

Pullen (2013, p. 17) argues that there is a risk of losing potentially important financial data when financial statement information is converted into a binary format. Therefore the second research question is:

Q2) Will a ranked scale calculation methodology, as opposed to a binary methodology, be effective in separating winners from losers (using only those signals shown to be relevant to the JSE)?

The null hypothesis, H_o:

A ranked scale calculation methodology is effective in separating winners from losers (using only those signals shown to be relevant on the JSE).

The alternate hypothesis, H1:

A ranked scale calculation methodology is not effective in separating winners from losers (using only those signals shown to be relevant on the JSE).

3.3 Research Question 3:

Advances in computing technology, and its impact on the dissemination of information, may have reduced the likelihood of discovering and exploiting price anomalies as more investors and fund managers have access to sophisticated tools which help to determine fair prices (Richardson, Tuna and Wysocki, 2010). A further challenge to accounting-based fundamental analysis stems from research into the field of behavioural finance that has sought to challenge the relevance of a purely rational approach to pricing (Hirshleifer, 2001). Research question three is therefore:

Q3) Has accounting-based fundamental analysis, in the form of the PiotroskiTrfm F-score, become less effective in separating winners from losers on the JSE?

The null hypothesis, H_o:

The PiotroskiTrfm F-score's ability to separate winners from losers on the JSE has decreased over time.

The alternate hypothesis, H1:

The PiotroskiTrfm F-score's ability to separate winners from losers on the JSE has not decreased over time.

4. Research Methodology

4.1 Research Design

This research consisted of two main parts. The first part examined the relevance of the F-score's nine signals in identifying winners from losers on the JSE. The second part proceeded to transform the F-score by amending the simplistic binary methodology to achieve a scaled ranking of companies for each of the relevant signals. Further analysis of the results obtained allowed for the answering of research question three, namely whether the F-score became less effective over time.

The research methodology followed was therefore a quantitative study as the data required to perform the research was entirely quantitative and was processed using a research design developed prior to the actual research (Adams, Khan, Raeside & White, 2007, p. 2). The research philosophy adopted was direct realism and the approach was deductive as it involved the design of research questions from an existing theory. The research strategy was designed to test the research questions and the results of the study indicated whether or not an existing theory would require modification (Saunders & Lewis, 2012, p.108).

The research took the form of an explanatory study in that it investigated the relationship between a company's F-score and its share price performance and attempted to examine how the relationship changed with an amended F-Score calculation methodology. The research therefore attempted to discover causal relationships between key variables (Saunders & Lewis, 2012, p. 113).

The research strategy followed the form of an experiment to study the causal links between independent and dependent variables. (Saunders & Lewis, 2012, p. 114). While experimental research is best suited for explanatory research (Bhattacherjee, 2012, p. 83) this was an ex-post facto study and therefore no control could be exercised over dependent variables such as company accounting data and share prices. This diminished the causal nature of the study (van der Merwe, 2012, p. 28). A mono method was applied to answer the research questions as all data was processed and analysed using the strategy outlined above. As the research focused on the aggregate relationship between the dependent and independent variables, as opposed to a trend, it was designed as a cross-sectional study (van der Merwe, 2012, p. 29).

4.2 Population

The population of this research was different for its two main parts. Part one tested the F-score's nine signals individually to determine their relevance in separating winners from losers on the JSE. The population consisted of all stocks listed on the main board of the JSE for which the required financial statement data was available.

The second part of the research introduced a revised calculation methodology for the F-score, based on a ranked scale approach, and applied it only to the signals that were found to be relevant in part one. The population for the second part consisted primarily of the largest 160 stocks, by market capitalisation, listed on the JSE for which the required data was available and was therefore similar to Muller and Ward (2013) and Viljoen (2017, p. 26). The largest 160 stocks represented approximately 99 percent of the JSE's total value over the chosen period (Muller & Ward, 2013). The limitation to the largest stocks by market capitalisation ensured the exclusion of a number of very small and illiquid stocks.

The population did however differ from Muller & Ward (2013) in one respect, namely if one of the largest 160 stocks did not have the required accounting data for a particular period it was replaced by the 161st largest stock. The limitation of 160 stocks served to avoid the inclusion of the smallest and most illiquid stocks in the portfolios that were subsequently formed.

For both part one and part two of the research newly listed shares were included in the quarter following their listing and delisted shares were excluded in the quarter following their delisting.

4.3 Unit of Analysis

The unit of analysis was individual stocks listed on the main board of the JSE throughout the sample period.

4.4 Sampling Frame

The sampling frame was all stocks listed on the main board of the JSE for the period 31 December 2004 to 31 October 2017 for which adequate financial statement data and stock prices were available. The main source of data was the Sharenet and INet BFA databases. As the study was wholly reliant on secondary data that was publically disclosed and independently verified, the need for ethical consideration was eliminated (Saunders & Lewis, 2012, p. 79).

The research therefore extended over a number of market cycles. The sample frame included the strong bull market from 2005 to June 2008, the sharp decline in market prices following the 2008 global financial crisis, the subsequent gradual recovery, as well as the recent period of extended negative sentiment that is, in part, attributed to political uncertainty and successive sovereign credit downgrades. Consideration was therefore given to the findings by Abarbanell and Bushee (1997) that fundamental signals are impacted by macroeconomic variables.

The sample frame therefore included data for 52 full quarters, up to 30 September 2017, as well as an additional month up to 31 October 2017.

4.5 Sampling Method

Stocks listed on the main board of the JSE with adequate financial statement data and stock prices from the Sharenet and INet BFA databases were identified for the period 31 December 2004 to 31 October 2017. However, as indicated, there was a variation in the population between the two main parts of the research.

4.5.1 Part One: Research Question 1

Research Question 1 sought to establish if all of the F-score's nine signals were relevant in separating winners from losers on the JSE. The sample for Research Question 1 included all shares listed on the main board of the JSE, for the chosen sample period, for which the required financial statement data was available.

Unlike in the case of Piotroski (2000), where F-scores were recalculated on an annual basis, this research followed the methodology applied by Pullen (2013) where scores were recalculated on a quarterly basis. While most scores would not experience dramatic changes over a 12 month period, as financial statements are only released annually, there may have been instances where share issuances or buy-backs during the year could have impacted on the EQ_OFFER signal and such changes were therefore accounted for in a timely manner.

As each of the nine signals were tested individually and separately from each other, only two portfolios were formed for each of the signals. The first portfolio consisted of shares where the company's financial data was considered positive for that particular signal (binary score of 1) while the second portfolio represented a negative signal (binary score of zero).

The trading strategy applied, namely three month buy-to-hold, was consistent with the quarterly recalculation of scores and portfolio formation. Dividends were included in share returns using the INET historical time series of dividend pay-outs (Muller & Ward, 2013). Trading fees were not taken into consideration as the intention of the research was not to establish exact returns but rather to investigate the F-score's underlying principles and signals.

4.5.2 Part Two: Research Questions 2 and 3

Research Question 2 sought to construct a transformed F-score (PiotroskiTrfm), using a ranked scale methodology, by only considering those signals shown to be relevant on the JSE as per the findings of Research Question 1. As already indicated, the population for this part of the research was limited to the top 160 stocks by market capitalisation for which the required information was available.

As in part one, the trading strategy applied, namely three month buy-to-hold, was consistent with the quarterly recalculation of scores and portfolio formation. Dividends were included in share returns however trading fees were once again not taken into consideration.

The transformed F-score was calculated by applying a ranking system that is standardised to real numbers between the ranges of 0 to 1. An outline of this method is provided in Table 4.

Table 4: Transformed F-score calculation methodology

Company	Signal: F_ΔMARGIN	Binary score		Ranking	Standardised to percentages	Real Score
Company A	80%	1		1	100%	1
Company B	50%	1		2	75%	0.75
Company C	-22%	0		4	25%	0.25
Company D	10%	1		3	50%	0.5

Once a ranked scale score was calculated for each of the relevant signals, the scores were combined to ascertain a company's PiotroskiTrfm score. The 160 transformed F-scores were divided into quintiles of 32 stocks each, representing the five portfolios.

Quintile 1 consisted of the highest PiotroskiTrfm scores and would therefore be the portfolio that was expected to deliver the highest returns. The equivalent of Quintile 1 in the case of the original binary F-score, where all nine signals were considered, would be a combined portfolio consisting of stocks that obtained scores of 8 and 9. In the case of this research, where only 6 signals were found to be relevant, a portfolio of stocks with a score of 6 would be the binary equivalent of Quintile 1. Table 5 outlines a comparison of the three different scores and their outputs:

Table 5: Comparison of F-score outputs

Methodology	High F-score	Low F-score
Original binary F-score (nine signals)	8 and 9	0, 1 and 2
JSE binary F-score (six relevant signals)	6	0 and 1
PiotroskiTrfm F-score (ranked scale methodology using six relevant signals)	Quintile 1	Quintile 5

The high and low score outputs of the PiotroskiTrfm score provided the required information to answer Research Question 2.

Research Question 3 relied on the observation of the relative relationship between the high and low score outputs from both the JSE binary score and the PiotroskiTrfm score to establish if their ability to separate winners from losers diminished over time during the sample period.

4.6 Data Analysis

Data analysis was performed by using Muller and Ward's (2013) StyleEngine. Not only has the StyleEngine been used for similar types of analyses of JSE data (Viljoen, 2016, p. 34; Shapiro, 2016, p. 34; Taljaard, Ward & Muller, 2015) but it allows for the formation of portfolios to reduce volatility in the data.

An important characteristic of the StyleEngine is that it measures the performance of portfolios using cumulative returns. This differs from the traditional use of t-tests to assess the significance of differences in portfolio returns. The traditional t-test approach is considered methodologically weak for this type of study and especially where multiple portfolios are compared with each other. Converting a portfolio's quarterly returns to log returns allows for the cumulative index (value) of each portfolio to be plotted over the sample period for visual comparison (Muller & Ward, 2013; Shapiro, 2016, p. 34).

A further advantage of the StyleEngine is that it was able to perform the scaled ranking of stocks, even when there was a non-linear relationship between the scores of a particular signal and the subsequent return. Where a linear relationship exists between the score of a particular signal and the subsequent share return it would be relatively easy to sort and rank companies from one end of the spectrum to the next. However, a non-linear relationship poses challenges as ranking could begin, and proceed along, any part of the database.

The StyleEngine applied ranked percentages in order to seek out the highest signal scores, for each of the relevant signals, where they were not necessarily located within the highest performing portfolio. The ranked percentages and their relation to returns are included in Annexure 2.

4.6.1 Analysis towards Research Question 1

Research Question 1 sought to identify whether all of the F-score's nine signals are relevant in separating winners from losers on the JSE over the sample period. In applying the methodology outlined above, two portfolios were constructed for each of the nine signals.

The first portfolio consisted of shares with a favourable signal score (binary score of 1) while the second portfolio contained shares with a negative signal (binary score of 0). The scores were recalculated on a quarterly basis and portfolios were rebalanced accordingly. Returns for each of the portfolios were reflected as cumulative log returns and plotted visually over the sample period.

The visual representation of the portfolio returns allowed for the analysis of data to establish whether:

- the positive signal portfolio (binary score 1) delivered superior returns to that of the negative signal portfolio (binary score 0);
- the returns of the positive signal portfolio were higher than the JSE All Share Index (J203T) as well as the JSE's top 160 shares by market capitalisation;
- the returns of the negative signal portfolio were lower than the JSE All Share Index (J203T) as well as the JSE's top 160 shares by market capitalisation; and the relative relationship between the cumulative returns of the two portfolios indicated an ability to separate winners from losers.

Once each of the nine signals were tested in the manner outlined above, it was possible to determine which of the signals were relevant to the JSE and, therefore, to answer Research Question 1.

4.6.2 Analysis towards Research Question 2

Research Question 2 assessed the revised calculation methodology of the PiotroskiTrfm F-score to establish whether it was effective in separating winners from loosers over the sample period. The method of analysis was similar to that of Research Question 1.

Ranked scores of the six relevant signals were calculated for each stock on a quarterly basis and combined into a PiotroskiTrfm F-score. The 160 PiotroskiTrfm F-scores were divided into quintile portfolios and cumulative log returns for each of the portfolios were plotted visually over the sample period.

The visual representation of the portfolio returns allowed for the analysis of data to establish whether:

- the Quintile 1 portfolio (highest PiotroskiTrfm F-scores) delivered superior returns to all other portfolios;
- the Quintile 1 portfolio delivered returns in excess of the J203T;
- the Quintile 5 portfolio (lowest PiotroskiTrfm F-scores) delivered the lowest returns of all the portfolios; and
- the Quintile 5 portfolio underperformed the J203T.

If the analysis indicated that all of the above conditions were true then it would imply that the PiotroskiTrfm F-score was able to separate winners from losers over the sample period. This analysis would enable to answering of Research Question 2.

4.6.3 Analysis towards Research Question 3

The analysis conducted to answer Research Question 2 was further extended in answering Research Question 3. The relative relationship between the cumulative log returns of the Quintile 1 and Quintile 5 portfolios were calculated and visually represented.

If the relative relationship of the cumulative returns showed a consistent and continued positive trend it would indicate that the PiotroskiTrfm F-score's ability to separate winners from losers did not diminish over the sample period. Conversely, a negative trend in the relationship of the cumulative log returns would indicate that the stock screen's effectiveness did diminish over time.

4.7 Research Limitations

While the study was designed as a causal study there are many factors that may influence the dependent variable. Therefore, as expressed by van der Merwe (2012, p. 40) the study should be viewed as a predictive study rather than one that can determine cause and effect with absolute certainty.

Transaction costs have not been accounted for in the quarterly rebalancing of portfolios and therefore the actual portfolio returns would have been lower than those detailed in this research. The inclusion of transaction costs may also have influenced the optimal holding and formation periods (Viljoen, 2016, p. 41).

The research spans a period during which South African listed companies converted their financial reporting standards from GAAP to IFRS. This conversion may have led to changes in financial reporting which could have an impact on the calculation of the F-score. This research will not investigate the impact of the conversion to IFRS and will assume the impact to be negligible as all companies within the sample were, by the nature of their listing on the JSE, required to convert to IFRS within similar periods.

A further limitation of the study stems from Broad Based Black Economic Empowerment (BBBEE) legislation that has required companies to transform their ownership structures. The different manner, degree to which, and timeframe over which companies have implemented the legislation would have resulted in different outcomes to the scoring of the EQ_OFFER signal. While an increase in the number of common shares in issue was considered a negative signal by Piotroski (2000), it could possibly be considered as a positive signal the context of BBBEE legislation and the varied financial and non-financial benefits that could accrue to a company.

As in the case of Shapiro (2016, p. 36), portfolios were constructed using an equal weighting. The use of a weighting based on market capitalisation may have produced different results.

This study was specifically designed to test the validity of the F-score’s signals on the JSE and all analyses were conducted in the context of such. A similar study in the context of a market with different characteristics may well have delivered different results. Therefore, the interpretation and application of the results are restricted to the JSE and specifically to the timeframe over which the research was conducted.

5. Results

The results presented follow the research questions and their respective hypotheses:

Q 1) Are all of the F-score's nine signals relevant in separating winners from losers on the JSE?

The null hypothesis, H_o:

Not all of the F-score's nine signals are relevant in separating winners from losers on the JSE.

The alternate hypothesis, H1:

All of the F-score's nine signals are relevant in separating winners from losers on the JSE.

Q 2) Will a ranked scale calculation methodology, as opposed to a binary methodology, be effective in separating winners from losers (using only those signals shown to be relevant to the JSE)?

The null hypothesis, H_o:

A ranked scale calculation methodology is effective in separating winners from losers (using only those signals shown to be relevant on the JSE).

The alternate hypothesis, H1:

A ranked scale calculation methodology is not effective in separating winners from losers (using only those signals shown to be relevant on the JSE).

Q 3) Has accounting-based fundamental analysis, in the form of the PiotroskiTrfm F-score, become less effective in separating winners from losers on the JSE?

The null hypothesis, H_o:

The PiotroskiTrfm F-score's ability to separate winners from losers on the JSE has decreased over time.

The alternate hypothesis, H1:

The PiotroskiTrfm F-score's ability to separate winners from losers on the JSE has not decreased over time.

5.1 Results for Research Question 1

5.1.1 Tests of F-score Signals

The F-score's nine signals were tested against all companies listed on the main board of the JSE for which the required accounting data was available. The main board would typically comprise more than 350 stocks (Muller & Ward, 2013) however companies were excluded when the required accounting data was unavailable or not presented in the required format.

Therefore, the main filter for this population was the existence of the required accounting data. In applying the filter, the StyleEngine generated an exception report for every quarter which lists the companies that were excluded and the reasons for their exclusion. An example of an exception report is provided in Appendix 1.

Two portfolios were constructed to test each signal in line with the binary calculation methodology. All companies with a positive signal (binary score 1) were included in a portfolio while those with a negative signal (binary score 0) comprised the second portfolio. The results for each of the nine signals are presented below in tabular format indicating each portfolio's cumulative log returns over the sample period as well as their average annual return.

The relative return between each portfolio was calculated by dividing the cumulative log return of the positive signal portfolio with that of the negative signal portfolio and then reflected as a percentage difference. The relative return is useful to assess the ability of the relevant signal in separating winners from losers.

Where appropriate, the information was also plotted to provide further support for the discussion. Annualised returns of the JSE All Share Index (J203T) as well as the JSE Top 160 index were included in graphs to assist in determining the ability of a signal to outperform the market. The relative relationship between the positive signal portfolio (binary score of one) in relation to the J203T index was also reflected.

While a more detailed discussion of the results follows in Chapter 6, it was necessary to provide a brief discussion of the results in this chapter to highlight the approach towards determining those signals considered relevant to the JSE.

5.1.1.1 Profitability signals

The data contained in Table 6 reflects that the signals F_ROA, F_CFO, and F_ACCRUAL are relevant to the JSE as the portfolios that received a score of 1 did outperform those that received a score of 0. F_CFO returned the largest relative relationship between the positive and negative portfolios followed by F_ROA. These signals were therefore able to separate winners from losers.

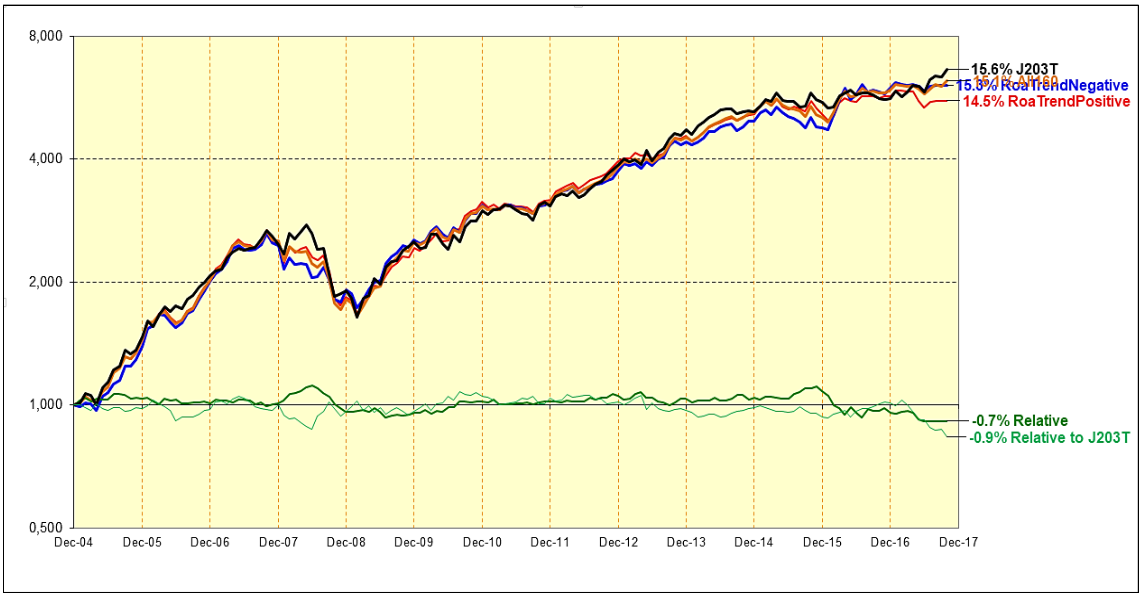
The signal F_ΔROA (change in return on assets) was counterproductive as the portfolio consisting of shares with a positive change in return on assets actually delivered slightly lower returns than the portfolio of companies with a negative change in return on assets.

Further analysis was conducted and, as reflected in Figure 1 below, the relative measure showed only slight movements and the difference in portfolio returns over the period were not significant. Therefore F_ΔROA was not considered to be a relevant signal for the separation of winners from losers on the JSE.

Table 6: Profitability signals portfolio returns

Signal	Portfolio (Binary Score)	Cum Log Returns	Annualised Portfolio Returns	Relative
F_ROA	ROAPositive (1)	6.46	15.9%	16.5%
	ROANegative (0)	0.93	-0.6%	
F_CFO	CFOPositive (1)	6.66	16.4%	18.0%
	CFONegative (0)	0.82	-1.6%	
F_ΔROA	RoaTrendPositive (1)	5.56	14.5%	0.7%
	RoaTrendNegative (0)	6.08	15.2%	
F_ACCRUAL	AccrualNegative (1)	6.21	15.5%	-2.3%
	AccrualPositive (0)	4.61	12.8%	

Figure 1: F_ΔROA portfolio returns



It is interesting to note that while both F_ROA and F_CFO showed a very strong ability to separate winners from losers, it was not necessarily the case for all periods during the sampling frame. As can be seen from the relative measure in Figure 2 and Figure 3, the signals were ineffective from the start of the sampling period up until the middle of 2008. During that initial period both the positive and negative portfolio returns were closely tracking the benchmark J203T. It was only at the point in which the market began to react to the 2008 global financial crisis where the relative measure of both signals started to reflect a significant difference.

Figure 2: F_ROA portfolio returns

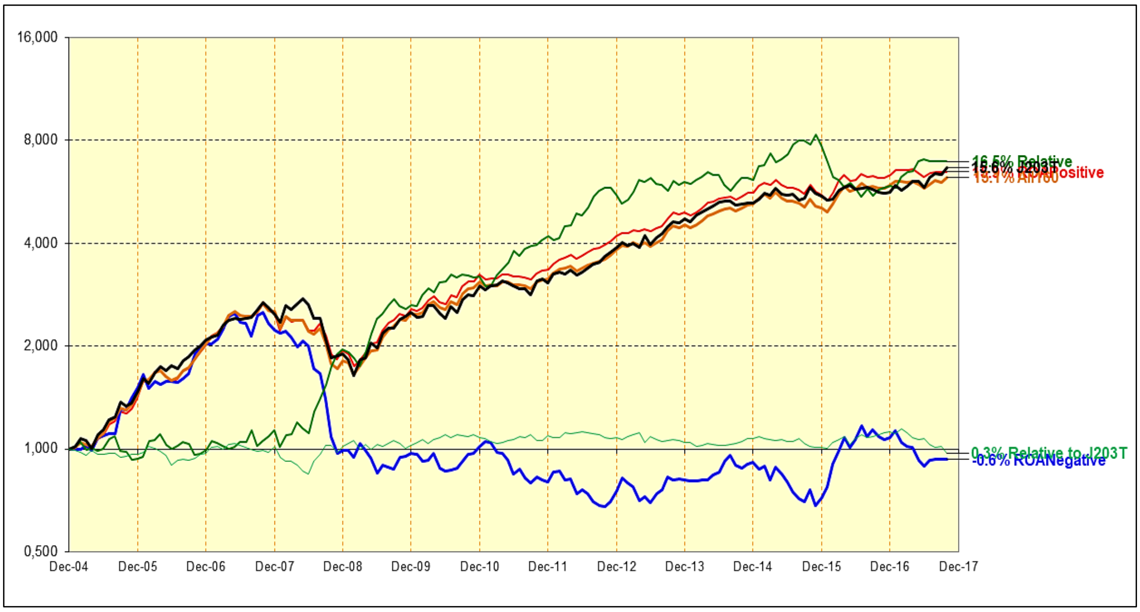
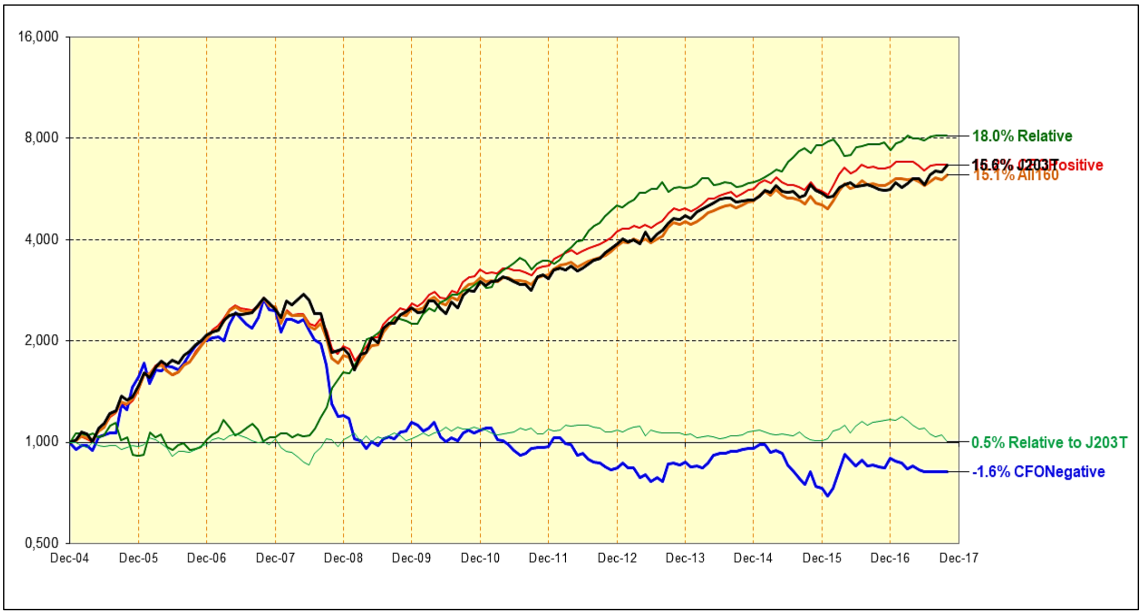
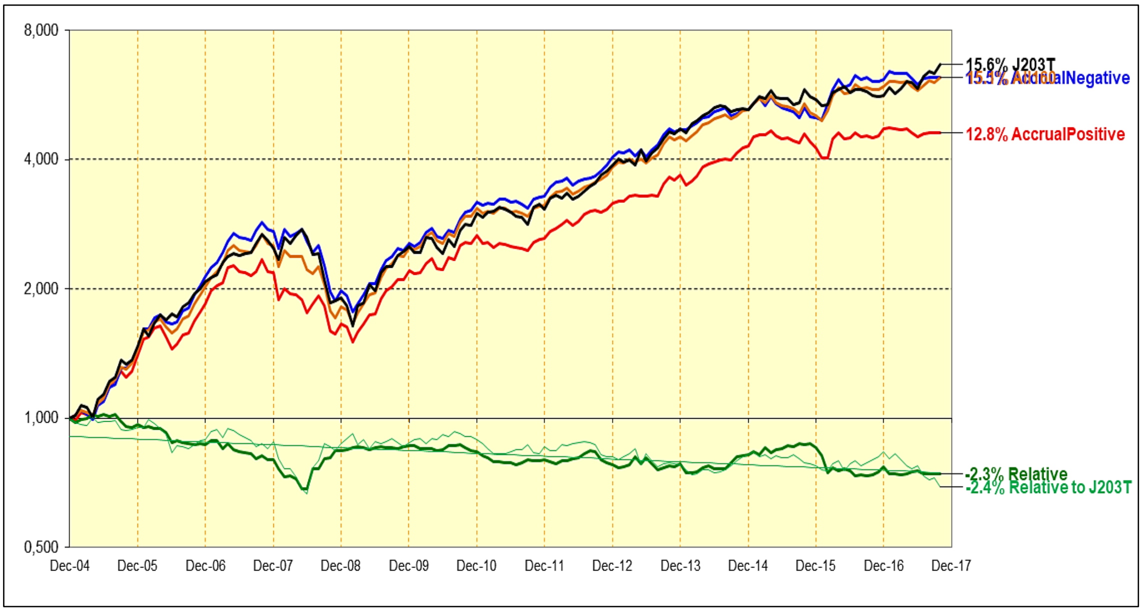


Figure 3: F_CFO portfolio returns



The F_ACCRUAL signal, is the only one of the nine signals where the relative relationship between the positive and negative portfolios reflects a clear trend throughout the sample period. Furthermore, Figure 4 shows that the portfolio relative also closely tracks the J203T relative throughout the period.

Figure 4: F_ACCRUAL portfolio returns



5.1.1.2 Capital structure and liquidity signals

The data in Table 7 reflects that only the EQ_OFFER signal was effective in separating winners from losers. As in the case of F_ΔROA, the F_ΔLIQUID portfolios reflected a relative measure with only slight movements over time and the difference in portfolio returns over the period were not significant (see Figure 5). Therefore the F_ΔLIQUID signal was not considered to be relevant to the JSE.

The F_ΔLEVER portfolios showed counterproductive results. As reflected in Figure 6, material differences in annualised portfolio returns are observed since December 2013 with no evidence of a reversal in the trend. The F_ΔLEVER signal is therefore considered to be relevant, however it performs in the opposite manner to Piotroski's (2000) original definition.

For the purposes of a JSE-relevant F-score, the allocation of binary scores to F_ΔLEVER portfolios were therefore switched around so that a negative trend would receive a score of zero and a positive trend would be allocated a score of 1.

Table 7: Capital structure and liquidity signals portfolio returns

Signal	Portfolio (Binary Score)	Cum Log Returns	Annualised Portfolio Returns	Relative
F_ΔLEVER	LeverageTrendNeg (1)	4.69	13.0%	1.5%
	LeverageTrendPos (0)	5.65	14.6%	
F_ΔLIQUID	LiquidityTrendPos (1)	5.63	14.6%	0.3%
	LiquidityTrendNeg (0)	5.43	14.3%	
EQ_OFFER	EquityIssueTrendNeg (1)	8.90	18.8%	4.2%
	EquityIssueTrendPos (0)	5.20	13.9%	

Figure 5 and Figure 6 reflect an interesting similarity between the relative measures of the F_ΔLIQUID and F_ΔLEVER signals. In both instances the relative measure remained flat from 31 December 2004 until the middle of 2013. This shows that the positive and negative portfolios of both signals tracked each other closely over that period. The positive portfolios of both signals also tracked the J203T closely over the same period.

Figure 5: F_ΔLIQUID portfolio returns

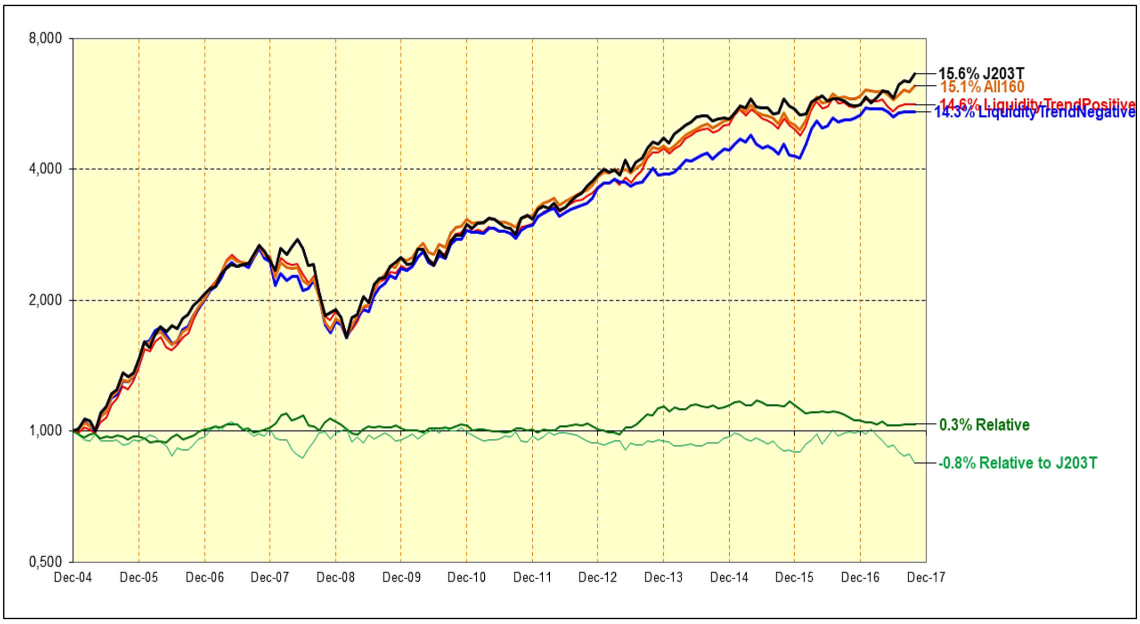
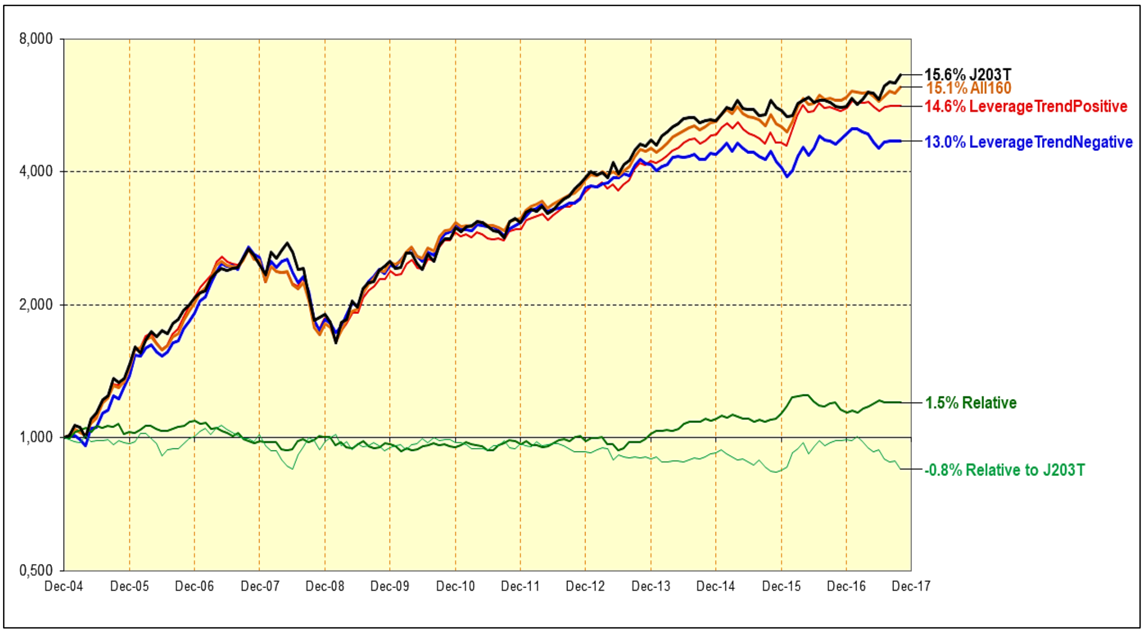
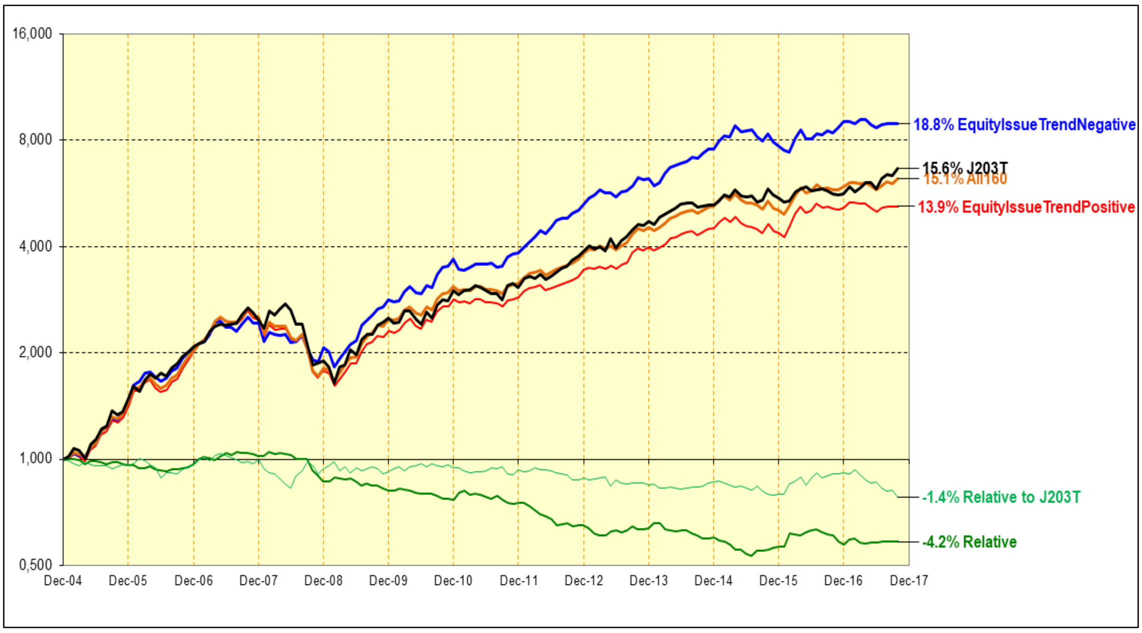


Figure 6: F_ΔLEVER portfolio returns



The F_EQOFFER portfolios appear to have behaved in a similar manner to those observed for the F_ROA and F_CFO signals in that they tracked each other and the J203T very closely until the middle of 2008 when the market started reacting to the global financial crisis.

Figure 7: EQ_OFFER portfolio returns



5.1.1.3 Operating efficiency signals

Table 8 reflects that while the F_ΔMARGIN signal was counterproductive in terms of annualised portfolio returns, the relative measure of 0.8% was low. Figure 8 shows that the relative measure remained constant for most of the sample period. There is no indication of a significant trend in the relative measure and therefore the F_ΔMARGIN signal is not considered to be relevant.

Portfolios for the F_ΔTURN signal reflected similar results to those of F_ΔLEVER in that they acted in opposition to their original scoring and a negative trend in the relative measure is observable since February 2012. The F_ΔTURN signal is therefore considered to be relevant however its scoring should be reversed.

Table 8: Operating efficiency signals portfolio returns

Signal	Portfolio (Binary Score)	Cum Log Returns	Annualised Portfolio Returns	Relative
F_ΔMARGIN	MarginTrendPos (1)	5.66	14.7%	0.8%
	MarginTrendNeg (0)	6.24	15.5%	
F_ΔTURN	EfficiencyTrendPos (1)	5.12	13.8%	2.2%
	EfficiencyTrendNeg (0)	6.81	16.0%	

Figure 8: F_ΔMARGIN portfolio returns

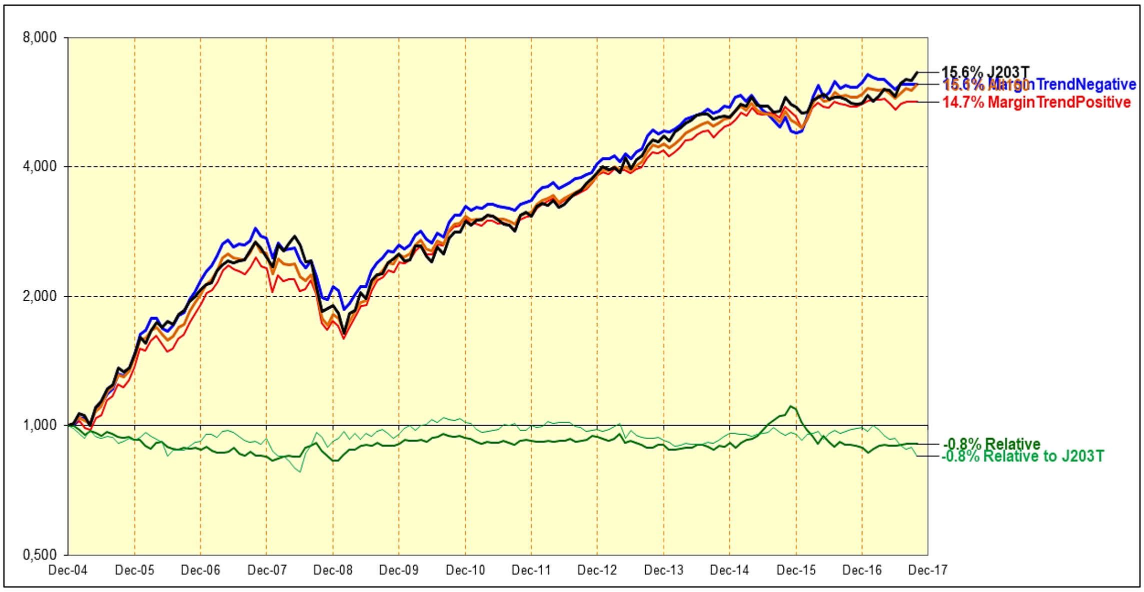
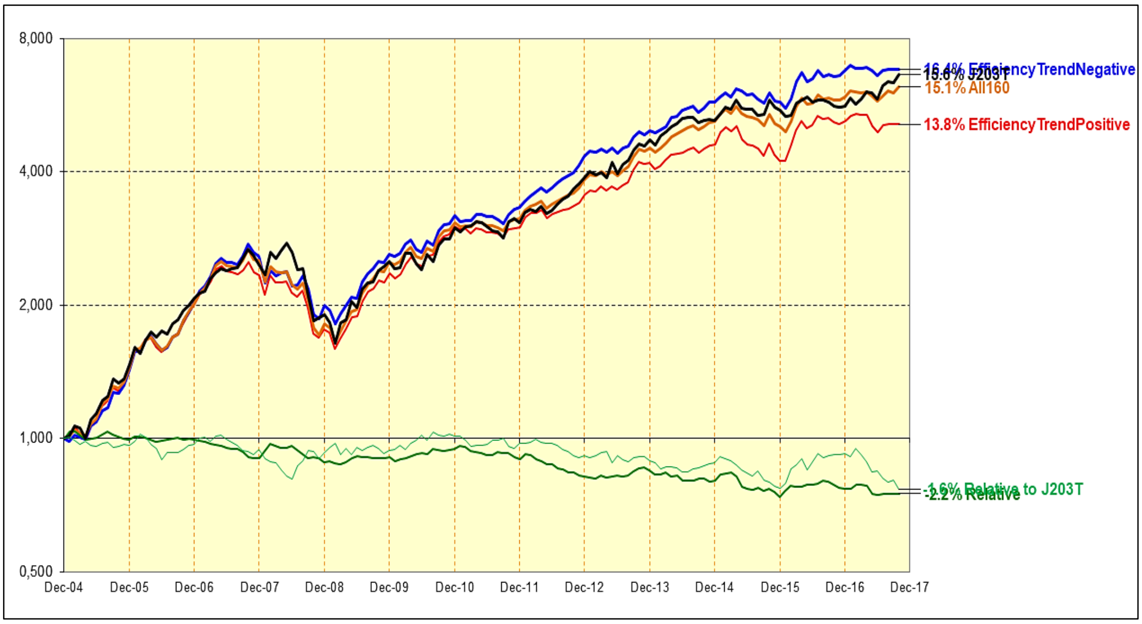


Figure 9: F_ΔTURN portfolio returns



5.1.1.4 JSE-relevant signals

The findings outlined above confirm that four of the nine signals were shown to be relevant on the JSE in the manner in which they were originally designed. These signals are F_ROA, F_CFO, F_ACCRUAL and EQ_OFFER.

Two signals, namely F_ΔLEVER and F_ΔTURN were found to be relevant but worked in the opposite manner in which they were originally intended. Two signals, namely F_ΔMARGIN and F_ΔLIQUID were not considered relevant to the separation of winners from losers on the JSE over the sample period.

The JSE-relevant F-score signals are reflected in Table 9.

Table 9: JSE-relevant F-score signals

Signal	Portfolios	Binary Score	Same as Piotroski (2000)
F_ROA	ROAPositive	1	Yes
	ROANegative	0	
F_CFO	CFOPositive	1	Yes
	CFONegative	0	
F_ACCRUAL	AccrualNegative	1	Yes
	AccrualPositive	0	
EQ_OFFER	EquityIssueTrendNegative	1	Yes
	EquityIssueTrendPositive	0	
F_ΔLEVER	LeverageTrendPositive	1	No – reversal of scoring
	LeverageTrendNegative	0	
F_ΔTURN	EfficiencyTrendNegative	1	No – reversal of scoring
	EfficiencyTrendPositive	0	

5.2 Results for Research Question 2

5.2.1 JSE-relevant binary F-score

Prior to the application of a ranked scale calculation methodology, the six signals found to be relevant in part one of the research were combined into a JSE-relevant binary F-score. This was done to confirm the validity of the findings in part one by observing the ability of the six identified signals to separate winners from losers once combined into a single score. The methodology applied in the calculation of the signals was the same as that reflected in Table 9. As only six signals were applied, seven portfolios were formed in line with the binary scores from zero to six.

The dataset consisted of the largest 160 stocks listed on the JSE by market capitalisation for the sample frame 31 December 2004, being the first date of portfolio formation, up to the final portfolio formation on 30 September 2017. Returns for the final portfolio formation were included up to 31 October 2017. The dataset therefore provided for 52 portfolio formations that occurred every quarter.

Table 10 provides descriptive statistics for the dataset. All portfolios were formed on each of the 52 quarters except for portfolio zero, that was only formed once, and portfolio 1 that was formed 36 times throughout the sample period. Portfolios zero, 1 and 2 all had a minimum size of 1 stock while portfolios 4 and 5 reflected the highest minimum stock numbers of 44 and 42 respectively. This trend is repeated for the maximum number of stocks in each portfolio as well as the mean portfolio size.

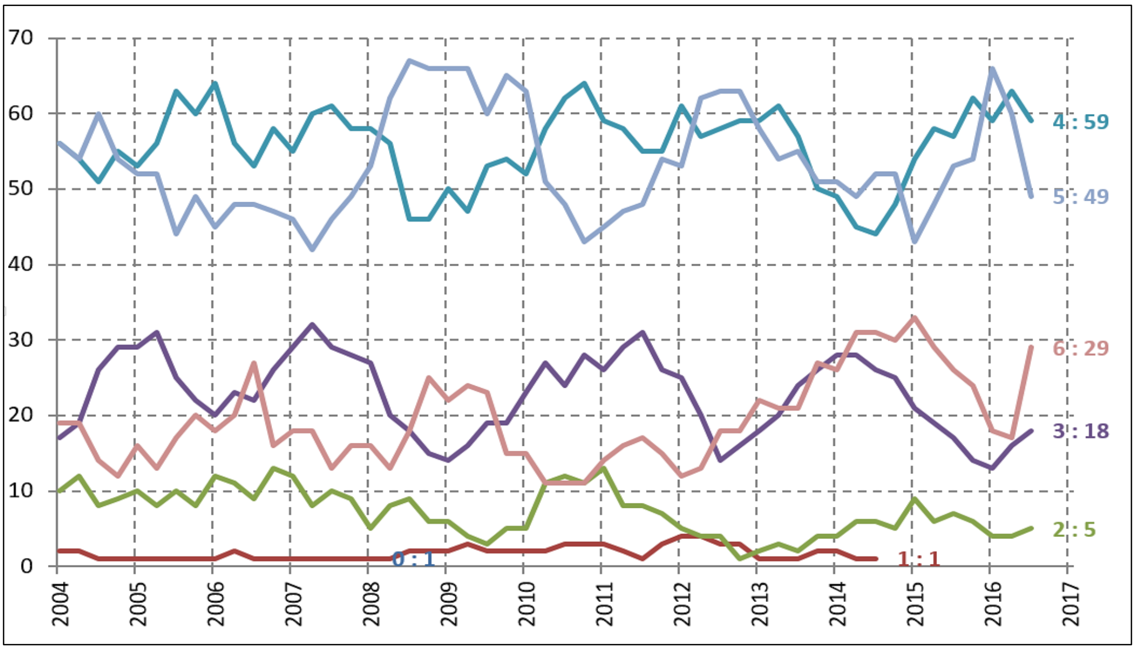
Table 10: Descriptive statistics Piotroski Binary

	Binary Portfolios						
	0	**1**	**2**	**3**	**4**	**5**	**6**
Number of formations	1	36	52	52	52	52	52
Minimum stocks	1	1	1	13	44	42	11
Maximum stocks	1	4	13	32	64	67	33
Mean portfolio size	1	2	7	22	56	53	19
Std Deviation	0	0.894	3.080	5.340	5.008	7.040	6.095

Figure 10 reflects the total number of stocks in each of the portfolios over the sample period with the numbers indicating the total number of stocks in each portfolio on the last date of portfolio formation. Figure 10 supports the data showing that the zero F-score portfolio (Piotroski0) was only formed once, on 31 December 2008, and with only one stock. The Piotroski1 portfolio was last formed on 30 June 2015 with only one stock. All other portfolios (Piotroski2 – Piotroski6) were formed in every quarter.

It is interesting to note that from December 2004 until December 2012, the distribution of stocks in portfolios 4 and 5 reflect an inverse relationship while, following that period, their changes in portfolio size tend to track each other more closely. This relationship is also observed between portfolios 3 and 6.

Figure 10: Distribution of stocks across binary portfolios



The annualised returns of each of the binary portfolios are reflected in Figure 11 below. Portfolio returns were once again calculated as cumulative log returns and expressed as annualised returns in the graph. No returns are shown for portfolios Piotroski7, 8 or 9 which confirms that only the six relevant signals were applied in the calculation of a stock's binary F-score.

It is observed that no movement on the Piotroski0 portfolio took place after 31 March 2009, three months following its only formation. Similarly no returns are registered for the Piotroski1 portfolio after September 2015. Both the Piotroski5 and Piotroski6 portfolios delivered an annualised return of 17.2% and outperformed the J203T that returned 15.9%.

While it is unwise to draw any inferences from the performance of Piotroski1 and Piotroski2, due to their small portfolio size, it interesting to note that they achieved positive returns in the lead up to the stock market crash in 2008 followed by consistently negative returns thereafter.

All other portfolios appear to have recovered from the market crash by the middle half of 2010, except for portfolio 3 which had only regained its losses in the first quarter of 2011. It is also observed the portfolio 6 consistently outperformed all other portfolios up until the first quarter of 2015, when it was closely tracked by portfolio 5.

When observing the ranking of the portfolios at the end of the sample period, it is worth noting that they follow the order in which they were expected to perform. Piotroski2, containing companies with the lowest F-score registered the lowest returns, is followed by Piotroski 3 and Piotroski4. The Piotroski5 and Piotroski6 portfolios, comprised of companies with the highest F-score also delivered the highest returns.

Figure 11: Piotroski binary portfolio returns

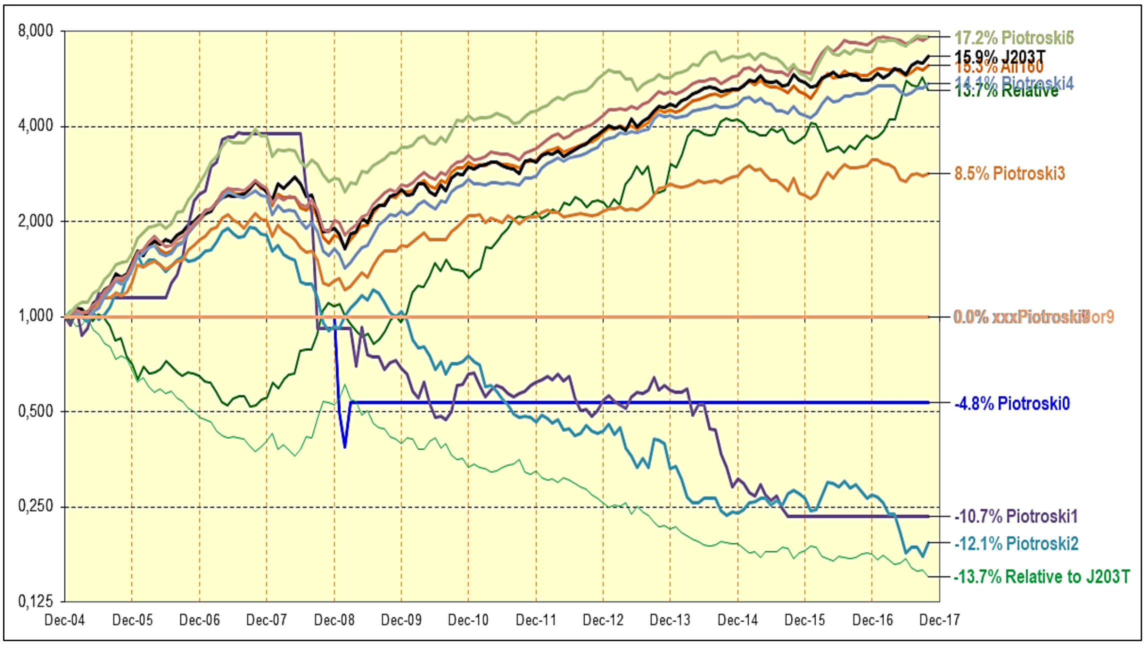
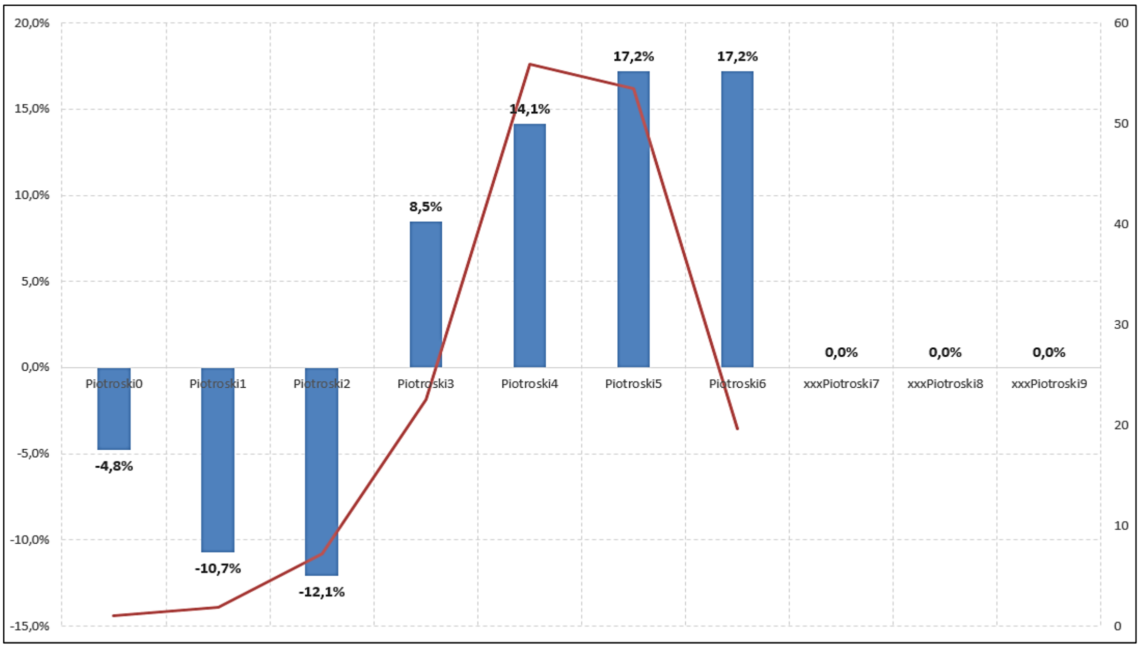


Figure 12 reflects the annualised return of each of the six portfolios together with the distribution of the mean portfolio size.

Figure 12: Mean portfolio size and annualised returns



5.2.2 PiotroskiTrfm F-score

Following the identification of the six relevant signals, the combination of those signals into a JSE-relevant binary F-score and obtaining sufficient evidence of a credible database, the research proceeded to apply a revised ranked scale calculation methodology to the relevant signals.

As already outlined, where a linear relationship existed between the score of a particular signal and the subsequent stock return it was relatively easy to sort and rank companies from one end of the spectrum to the next. However, a non-linear relationship required the application of ranked percentages in order to seek out the highest signal scores for each of the relevant signals. Once the ranked percentages had been applied, it was possible to rank stocks along a scale depending on the results from the calculation of each of the relevant signals. These results were then combined in order to obtain a stock's transformed F-score (PiotroskiTrfm).

As the scaled ranking of companies did not deliver a binary output, portfolios were not formed according to those observed in the JSE-relevant F-score. Instead, stocks were ranked and then divided into quintiles, where quintile 1 (PiotroskiTrfm1) contained the companies that had received the highest PiotroskiTrfm scores. The cumulative log returns of the PiotroskiTrfm portfolios are reflected in Table 11.

As in the case of the JSE-relevant F-score, the trading strategy applied, namely three month buy-to-hold, was consistent with the quarterly recalculation of scores and portfolio formation. Dividends were included in share returns however trading fees were once again not taken into consideration.

Table 11: Cumulative log returns PiotroskiTrfm portfolios

PTrfm1	PTrfm2	PTrfm3	PTrfm4	PTrfm5	J203T
12,84	9,50	4,38	5,95	2,09	6,66

Figure 13 plots the returns of the PiotroskiTrfm portfolios over the sample period. Each portfolio's cumulative log returns were converted to annualised returns. The relative relationship between the PiotroskiTrfm1 and PiotroskiTrfm5 portfolios is shown as well as the relative relationship between the PiotroskiTrfm1 portfolio and the J203T index.

Figure 13 shows a clear differentiation between the portfolios over the sample period. Stocks that had received the lowest scores constituted the PiotroskiTrfm5 portfolio which returned the lowest results while those in the top quintile delivered the highest returns. The results reflect a 15.2% premium over these two portfolios.

Both the PiotroskiTrfm1 and PiotroskiTrfm2 portfolios significantly outperformed the J203T index. The results reflect a premium of 5.2% for the PiotroskiTrfm1 portfolio over the J203T index.

It is interesting to note that, unlike in the case of the JSE-relevant binary F-score, returns delivered by the portfolios were not in all cases in line with F-score allocations. The PiotroskiTrfm4 portfolio consisted of stocks with lower ranked F-scores than the Piotroski3 portfolio, yet it delivered a higher annualised return.

Figure 13: PiotroskiTrfm portfolios

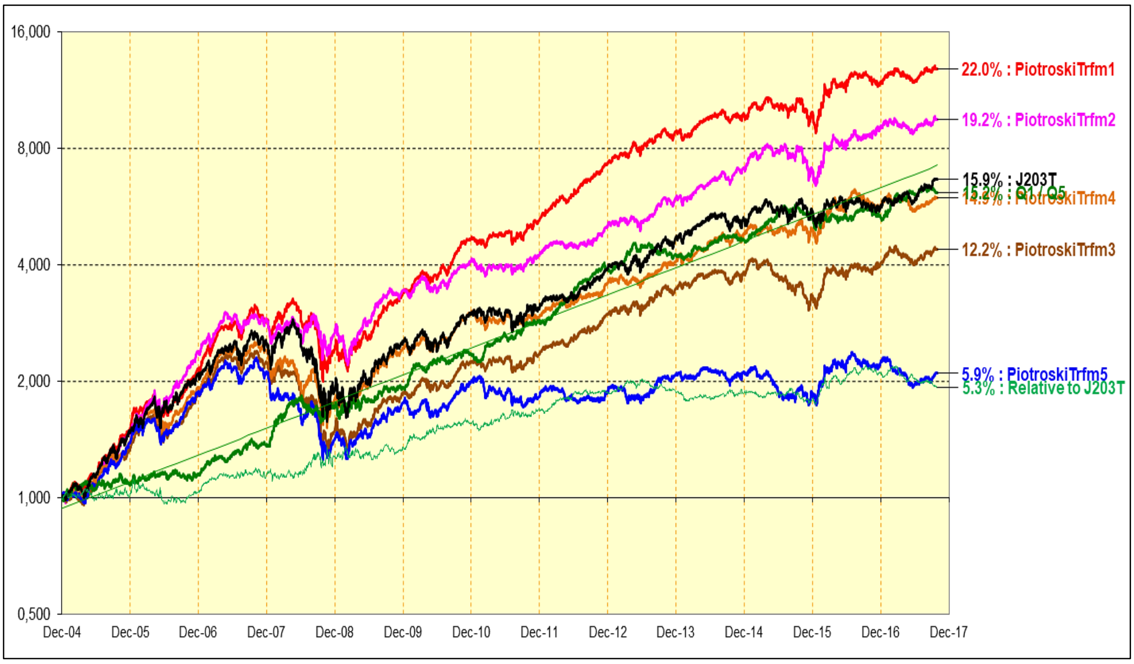
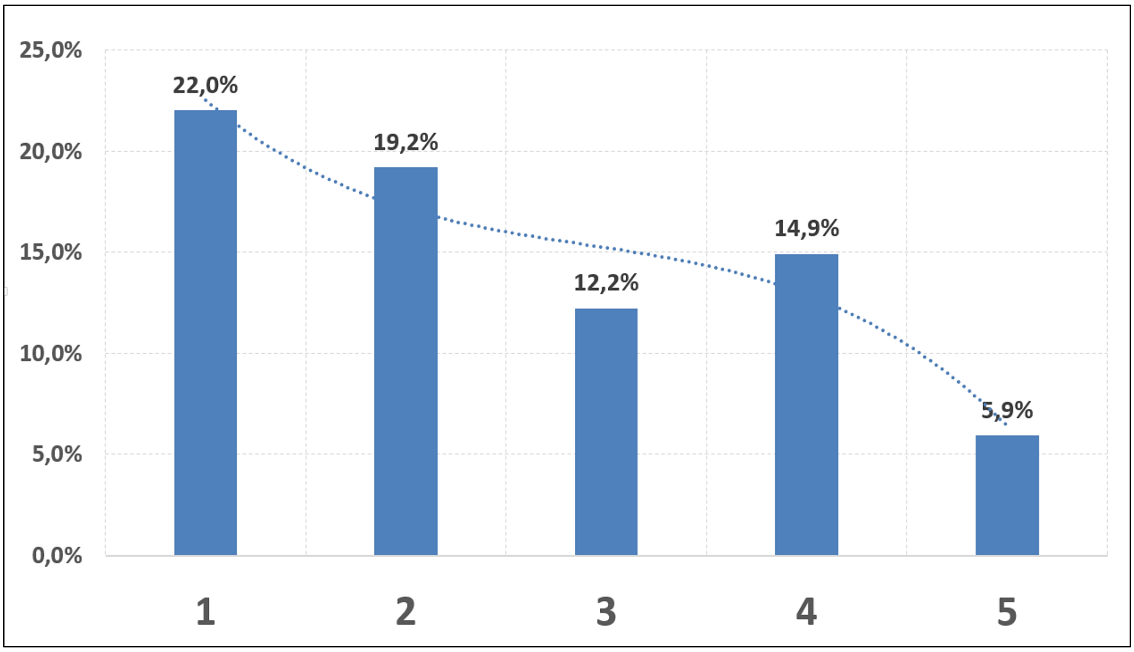


Figure 14: PiotroskiTrfm annualised portfolio returns



5.3 Results for Research Question 3

Research Question 3 serves to establish whether accounting-based fundamental analysis, in the form of the F-score, became less effective over time.

The results for Research Question 3 are presented in the relative relationship between the cumulative log returns of highest ranked PiotroskiTrfm stocks (quintile 1) and those of the lowest ranked (quintile 5). This relationship has been plotted in Figure 13 and reflects a premium of 15.2% per annum. However, it is not the annualised return in itself that is relevant to answering the research question. Of importance is the behaviour of the relative's trend over time and whether there is any evidence to suggest that the trend is in decline. The relative reflects a very constant ability to separate winners from losers with no evidence of a change in the trend.

6. Discussion of Results

The results provided in Chapter 5 are discussed below. Significant differences in the relevance of the F-score's nine signals in the context of the JSE were observed. The application of a ranked scale methodology to those signals found to be relevant, delivered results which conclusively prove the PiotroskiTrfm F-score's ability to separate winners from losers on the JSE. There was no evidence to suggest that the relevance of accounting-based fundamental analysis, as applied by the PiotroskiTrfm F-score, declined over the sample period.

6.1 Discussion Concerning Research Question 1

Research Question 1 sought to identify whether all of the F-score's nine signals were relevant in separating winners from losers on the JSE over the sample period. In order to answer the research question, two portfolios were constructed for each of the nine signals.

The first portfolio consisted of shares with a favourable signal score (binary score of 1) while the second portfolio contained shares with a negative signal (binary score of 0). The scores were recalculated on a quarterly basis and portfolios were rebalanced accordingly. Returns for each of the portfolios were reflected as cumulative log returns and plotted visually over the sample period.

The visual representation of the portfolio returns allowed for the analysis of data to establish whether:

- the positive signal portfolio (binary score 1) delivered superior returns to that of the negative signal portfolio (binary score 0);

- the returns of the positive signal portfolio were higher than the JSE All Share Index (J203T) as well as the JSE's top 160 shares by market capitalisation;

- the returns of the negative signal portfolio were lower than the JSE All Share Index (J203T) as well as the JSE's top 160 shares by market capitalisation; and the relative relationship between the cumulative returns of the two portfolios indicated an ability to separate winners from losers.

The results for each signal are now further discussed.

6.1.1 F_ROA

The signal relates to a company's return on assets. It was calculated by dividing net income (before any extraordinary items) by average total assets (average value of total assets for the previous and current financial years). If the company had a positive return it was allocated a score of 1. A negative return received a score of 0.

The ROAPositive portfolio delivered returns of 15.9% per annum which was slightly higher than that of the J203T, while the ROA negative portfolio reflected returns of 0.6%. The relative premium between the two portfolios was therefore 16.5% which was the second highest of all the signals. F_ROA was therefore shown to have a very strong ability to separate winners from losers and was determined to be relevant to the JSE.

However, this ability was not uniform throughout the period of the study and only began to reflect significance as the market declined in response to the global financial crisis of 2008. In the subsequent period of market recovery the relative relationship between the two portfolios continued to reflect a growing premium up until December 2015 when returns on the ROA negative portfolio improved. However, once the returns of ROANegative portfolio began to decline in December 2016, the positive relative trend continued. The findings therefore support the assertions made by Abarbanell and Bushee (1997) and Lev and Thiagarajan (1993) that changes to macroeconomic variables, and therefore conditions in different markets and over different periods, do have an impact on the relationship between signals and earnings.

6.1.2 F_CFO

The F_CFO signal measured whether or not a company had a positive cash flow during a particular financial year. A positive cash flow received a binary score of 1 while a negative cash flow would receive a score of zero.

The F_CFO measure reflected similar results to those of the F_ROA signal. Its positive portfolio delivered annualised returns of 16.4% while the relative premium between its two portfolios was 18% - the highest of all the signals. As in the case of F_ROA, the relative measure only started to show a significant difference in middle 2008.

The results would indicate that investors who wish to apply the lowest number of the nine signals should focus their analysis on F_ROA and F_CFO. This is in sharp contrast to the findings of Piotroski (2000) that these two measures lacked statistical significance in their association with future returns.

6.1.3 F_ΔROA

The F_ ΔROA signal represents the annual change in a company's return on assets. A positive change received a score of 1 while a negative change was allocated a score of zero. The signal F_ΔROA signal was found to be counterproductive as the portfolio consisting of shares with a positive change in return on assets actually delivered slightly lower returns than the portfolio of companies with a negative change in return on assets. However, the relative measure showed only slight movements and the difference in portfolio returns over the period were not significant. F_ΔROA was not considered to be a relevant signal for the separation of winners from losers on the JSE.

It should be noted that the signal was initially intended for application to value stocks, which are usually firms experiencing financial distress (Chen & Zhang, 1998). A one year negative change in the ROA would be significant to a firm that is already in financial distress and therefore the measure is more inclined to identify losers than winners. The fact that the JSE has a relatively small value stock universe (Van Der Merwe, 2012) may provide insight into why the signal was not considered relevant. It is interesting to note that Piotroski (2000) found that the signal lacked statistical significance in their association with future returns.

6.1.4 F_ACCRUAL

The F_ACCRUAL signal measures whether net income (before extraordinary activities) is less than cash flows from operations. It serves as an indicator of the firm's future ability to generate profits. If net income is less than cash flows then the company will receive a score of one, if it is more than cash flows then a score of zero was applied.

The F_ACCRUAL signal was the only one of the nine signals where the relative relationship between the positive and negative portfolios reflected a clear trend throughout the sample period. The relative trend is negative due to the fact that a positive answer to the signal would have resulted in a zero score, and therefore the signal is measured in the opposite manner to others such as ROA. The signal was found to be relevant to the JSE.

6.1.5 F_ΔLEVER

The F_ΔLEVER signal measured the year-on-year change in total long-term debt divided by average total assets. An increase in the ratio scored zero while a decrease scored 1. The F_ΔLEVER portfolios showed counterproductive results. Material differences in annualised portfolio returns were observed since December 2013 with no evidence of a reversal in the trend. The F_ΔLEVER signal was therefore considered to be relevant, however it performed in the opposite manner to Piotroski's (2000) original definition.

As in the case of F_ ΔROA, the signal would have a significant impact on firms that are in financial distress. This is supported by Piotroski's (2000) finding that the signal displayed a strong associations with future returns based on the value stock population in which it was applied.

However, for firms that are able to raise long-term debt for use as working capital the measure may be counterproductive when the cost of such debt is significantly lower than the market risk premium demanded by investors. It would therefore appear that companies listed on the JSE for the sample period raised long term debt and that enabled them to generate returns in excess of the cost of the debt.

6.1.6 F_ΔLIQUID

The signal measured the year-on-year change in the firm's current ratio represented by total current assets divided by total current liabilities. An increasing current ratio was considered positive and received a score of 1 whereas a decreasing current ratio was awarded a zero.

F_ΔLIQUID portfolios reflected a relative measure with only slight movements over time and the difference in portfolio returns over the period were not significant. Therefore the F_ΔLIQUID signal was not considered to be relevant to the JSE.

6.1.7 EQ_OFFER

An increase in the number of common shares in issue is considered a signal that the firm was unable to generate sufficient internal funds to service future opportunities and obligations. Therefore any increase in the number of common shares in issue was allocated a score of zero.

The signal appears to have performed in the manner originally intended and supports the view that the issuing of shares is negatively correlated with future stock returns (Daniel & Titman 2006; Daniel & Titman 2016). The signal was therefore considered relevant within the context of the JSE. While the signal's association with future returns was not as strong as in the case of Piotroski (2000) its ability to separate winners from losers on the JSE was significant.

6.1.8 F_ΔMARGIN

The signal measures the year-on-year change in the firm's gross margin (gross profit divided by revenue). An increase in the gross margin was awarded a score of 1 while a decrease resulted in a zero.

While the signal was shown to be counterproductive in terms of annualised portfolio returns, the relative measure of 0.8% was low and remained constant for most of the sample period. There was no indication of a significant trend in the relative measure and therefore the F_ΔMARGIN signal was not considered to be relevant to the JSE.

As in the case of F_ ΔROA, the signal would have a significant impact on firms that are in financial distress and where a negative change over a one year period would pose a risk. However, as the signal was not applied to a value stock population the finding can be defended from literature.

6.1.9 F_ΔTURN

The signal measures the year-on-year change in the firm's asset turnover (total revenue divided by total average assets). An increase in the asset turnover ratio was awarded a score of 1 while a decrease resulted in a zero.

Portfolios for the F_ΔTURN signal reflected similar results to those of F_ΔLEVER in that they acted in opposition to their original scoring and a negative trend in the relative measure was observable since February 2012. The F_ΔTURN signal was therefore considered to be relevant however its scoring should be reversed. This is an interesting finding as Piotroski (2000) identified the signal as having a strong association with future returns.

When applied over a one year period to firms in financial distress it would make sense that a drop in total revenue while maintaining the same asset base would pose a threat. Similarly, an increase in assets without the required increase in revenue would place strain on a company's cash flow. However, this is not the case for companies who are able to purchase assets that will realise commensurate revenues following a one year period.

6.1.10 Summary

The discussion outlined above confirms that four of the nine signals were shown to be relevant on the JSE in the manner in which they were originally designed. These signals are F_ROA, F_CFO, F_ACCRUAL and EQ_OFFER.

Two signals, namely F_ΔLEVER and F_ΔTURN were found to be relevant but worked in the opposite manner in which they were originally intended. Two signals, namely

F_ΔMARGIN and F_ΔLIQUID were not considered relevant to the separation of winners from losers on the JSE over the sample period.

The findings therefore support the assertions made by Abarbanell and Bushee (1997) and Lev and Thiagarajan (1993) that changes to macroeconomic variables, and therefore conditions in different markets and over different periods, do have an impact on the relationship between signals and earnings.
The observation that signals behaved differently during different periods of the sample frame, especially as observed with F_ROA and F_CFO further support the literature in this regard.

Research Question 1 and its associated hypotheses are outlined below.

Q 1) Are all of the F-score's nine signals relevant in separating winners from losers on the JSE?

The null hypothesis, H_o:
Not all of the F-score's nine signals are relevant in separating winners from losers on the JSE.

The alternate hypothesis, H1:
All of the F-score's nine signals are relevant in separating winners from losers on the JSE.

The findings regarding Research Question 1 indicate that not all of the F-score's signals are relevant in separating winners from losers on the JSE. This research therefore fails to reject the null hypothesis.

6.2 Discussion Concerning Research Question 2

Research Question 2 assessed the revised calculation methodology of the PiotroskiTrfm F-score to establish whether it was effective in separating winners from loosers over the sample period. The method of analysis was similar to that of Research Question 1.

Ranked scores of those signals found to be relevant in part one of the research were calculated for each stock on a quarterly basis and combined into a PiotroskiTrfm F-score.

The 160 PiotroskiTrfm F-scores were divided into quintile portfolios and cumulative log returns for each of the portfolios were plotted visually over the sample period.

The visual representation of the portfolio returns allowed for the analysis of data to establish whether:

- the Quintile 1 portfolio (highest PiotroskiTrfm F-scores) delivered superior returns to all other portfolios;
- the Quintile 1 portfolio delivered returns in excess of the J203T;
- the Quintile 5 portfolio (lowest PiotroskiTrfm F-scores) delivered the lowest returns of all the portfolios; and
- the Quintile 5 portfolio underperformed the J203T.

The results contained in Table 11, Figure 13 and Figure 14 serve to inform the discussion that follows. As the research sought to assess the ability of the PiotroskiTrfm F-score to separate winners from losers, the discussion will focus on the relevant portfolios, namely PiotroskiTrfm1 and PiotroskiTrfm5.

6.2.1 PiotroskiTrfm1 portfolio

The PiotroskiTrfm portfolios reflect a clear differentiation between their respective annualised returns. The portfolio containing stocks with the highest F_score, namely PiotroskiTrfm1 showed cumulative log returns of 12.84 as at 31 October 2017 which was annualised to 22%. The J203T index delivered cumulative log returns of 6.66 reflected as 15.9% per annum. There was therefore a premium of 5.9% for the portfolio over the J203T index.

Prior to the stock market's decline in response to the global financial crisis, the portfolio achieved its highest cumulative log return, namely 3.26, on 19 May 2008 and was the highest performing portfolio. PiotroskiTrfm2, had the second highest cumulative log return of 2.93. Following this date the portfolio closely tracked Piotroski2 until the middle of 2010 from when a significant difference in returns can be observed. Since that period, the portfolio has delivered the highest returns. The portfolio size was maintained at 32 stocks, with the highest PiotroskiTrfm ranking, throughout the sample period.

6.2.2 PiotroskiTrfm5 portfolio

The portfolio only delivered cumulative log returns of 2.09 as at 31 October 2017, which is expressed as an annualised return of 5.9%. During the period December 2004 to December 2009 the portfolio closely tracked PiotroskiTrfm3, however significant differences in returns can be observed for the subsequent period. From December 2005 to the end of the sample period the portfolio registered the lowest returns. The portfolio size was maintained at 32 stocks, with the lowest PiotroskiTrfm ranking, throughout the sample period.

6.2.3 PiotroskiTrfm1/PiotroskiTrfm5 relative

The relative between the two portfolios reflects a significant premium of 15.2% per annum. While the relative line in Figure 13 does reflect deviations from the upward trend, these are only observed in the periods:

- December 2005 - December 2006;
- August 2008 – November 2008;
- August 2013 – February 2014; and
- November 2015 – December 2016.

The relative relationship between the returns generated by the PiotroskiTrfm1 and PiotroskiTrfm2 portfolios, its trend line and the premium of 15.2% proves that the revised calculation methodology was able to separate winners from losers over the sample period.

6.2.4 PiotroskiTrfm F-score and JSE-relevant binary F-score

While it was not the purpose this research to compare the JSE-relevant binary F-score with its ranked scale equivalent, some interesting observations can be made regarding the portfolio performance of the two methodologies.

The first observation is that the binary portfolio containing the highest F-score stocks (Piotroski6) delivered a return of 17.2% per annum and was outperformed by its transformed version (PiotroskiTrfm1) with a 22% annualised return.
A further important observation was that there was no differentiation in the returns delivered between the binary Piotroski6 and Piotroski5 portfolios, while this was not the case between the two highest ranked transformed portfolios. It would therefore appear that the ranked scale methodology was better able to differentiate between winners from companies that obtained relatively high F-scores.

Visual observation would suggest that the binary F-score was better able to differentiate between losers amongst stocks that had low F-scores. However this observation must be considered within the context of very low portfolio sizes and infrequent formations for portfolios Piotroski0 and Piotroski1. Even though the Piotroski2 portfolio was formed in every quarter during the sample period it only reflected a mean portfolio size of seven stocks.

Combining the binary portfolios into two, namely Piotroski0-3 and a second portfolio of Piotroski4-6, would serve to provide a more realistic idea of the binary F-score's ability to separate winners from losers. By calculating a relative annual return based on median portfolio sizes one would observe an annualised return of 2.4% for Piotroski1-3 while the Piotroski4-6 portfolio would deliver 15.87% per annum. It would therefore appear, by this measure, that the ranked scale F-score was better able to separate winners from loosers than its binary counterpart. However, further testing of the two methods across different periods and on different markets should be undertaken before conclusive findings are reached.

6.2.5 Summary

Research Question 2 served to assess whether a ranked scale calculation methodology, applied only to those signals found to be relevant on the JSE, would be successful in separating winners from losers. The associated hypothesis were:

The null hypothesis, H_o:

A ranked scale calculation methodology is effective in separating winners from losers (using only those signals shown to be relevant on the JSE).

The alternate hypothesis, H1:

A ranked scale calculation methodology is not effective in separating winners from losers (using only those signals shown to be relevant on the JSE).

Based on the findings and the discussion thereof, the PiotroskiTrfm was able to conclusively separate winners from losers on the JSE. Therefore, this research failed to reject the null hypothesis.

6.3 Discussion Concerning Research Question 3

Research Question 3 and its associated hypothesis are outlined below:

Q 3) Has accounting-based fundamental analysis, in the form of the PiotroskiTrfm F-score, become less effective in separating winners from losers on the JSE?

The null hypothesis, H_o:

The PiotroskiTrfm F-score's ability to separate winners from losers on the JSE has decreased over time.

The alternate hypothesis, H1:

The PiotroskiTrfm F-score's ability to separate winners from losers on the JSE has not decreased over time.

The discussion contained in section 6.2.3 has detailed that there is no evidence to suggest that the ability of the PiotroskiTrfm F-score in separating winners from losers on the JSE declined during the sample period. This research has therefore rejected the null hypothesis and accepted the alternate hypothesis.

The findings prove that accounting-based fundamental analysis remains relevant on the JSE and that the threat of technological advances (Richardson, Tuna & Wysocki, 2010) has not served to diminish its effectiveness – at least not yet.

No findings can be made on whether a purely rational approach would have delivered better results to one that incorporated behavioural finance research as envisaged by Hirshleifer (2001). However this research does reject the statement by Marks (2011, p. 1) that "investing can't be reduced to an algorithm and turned over to a computer".

7. Conclusion

The purpose of the research was to expand on prior work conducted in the field of accounting-based fundamental analysis by assessing the relevance of the F-score's nine signals within the context of the JSE. The research also attempted to assess the application of a modified F-score calculation methodology to establish if it would be successful in separating winners from losers. The research consists of two major parts.

The first part of the research examined the relevance of the F-score's nine signals in identifying winners from losers on the JSE. The scope of the research included shares listed on the JSE for the period 31 December 2004 to 31 October 2017. Each signal's predictive capability was separately assessed using Piotroski's (2000) binary calculation methodology. Signals that were shown to be relevant for the chosen population were combined into a revised JSE-relevant F-score that also made us of the original binary approach.

The decision not to apply an initial value stock screen was informed by the argument on the limitations of the JSE's small value stock universe (Pullen, 2013, p. 5) as well as research indicating that the F-Score could be applied to both value and growth stocks (Piotroski, 2004; Zhou & Tice, 2011; Mohr, 2012).

The second part of the research proceeded to transform the F-score by amending the simplistic binary methodology to achieve a scaled ranking of companies. Only those signals found to be relevant in part one of the research were included in the transformed F-score. An assessment was then conducted on the ability of the revised calculation approach in separating winners from losers on the JSE for the sample period.

Finally, an analysis of the results of this research was used to assess the ongoing relevance of accounting-based fundamental analysis on the JSE. The research was conducted in light of the challenge posed by behavioural finance research, and specifically the criticism of a purely rational approach (Hirshleifer, 2001) as well as technological advances that threaten to undermine its foundational theory (Richardson, Tuna & Wysocki, 2010).

7.1 Principal Findings

This research makes important findings with regards to the application of the Piotroski F-score on the JSE and the ongoing relevance of accounting-based fundamental analysis.

The research sought to ask three questions, namely:

Q 1) Are all of the F-score's nine signals relevant in separating winners from losers on the JSE?

Q 2) Whether a ranked scale calculation methodology, applied only to those signals found to be relevant on the JSE, would be successful in separating winners from losers?

Q 3) Has accounting-based fundamental analysis, in the form of the F-score, become less effective in separating winners from losers on the JSE?

In line with the research questions, the findings are summarised as follows:

1) Not all of the F-score's nine signals were found to be relevant in separating winners from losers on the JSE. Three of the signals were found to have little or no predictive ability while two of the signals were found to be counterproductive in the manner in which Piotroski (2000) applied them.

2) A revised F-score calculation methodology (PiotroskiTrfm), applied only to those signals found to be relevant to the JSE, was successful in separating winners from losers over the sample period. A portfolio consisting of the highest PiotroskiTrfm scores would have delivered an annual return of 22% over the sample period while the lowest scoring PiotroskiTrfm portfolio only generated

annual returns of 5.9%. The relative between the two portfolios reflects a significant premium of 15.2% per annum.

3) No evidence was presented to suggest a decline in the ability of accounting-based fundamental analysis, as applied by the F-score, to separate winners from losers on the JSE.

This research finds that the conclusion reached by Ou and Penman (1989), namely that financial statements capture fundamentals that are not reflected in prices, is still relevant following almost three decades of technological advancement. The findings also support the argument that a purely rational approach is still successful in beating the market and that the results are not achieved by chance, but instead, stem from the mispricing of stocks (Yan & Zheng, 2017).

7.2 Implications of the Research

The research has found that accounting-based fundamental analysis remains relevant to the JSE despite the opposition to its purely rational approach. The implications of the research should be an encouragement to academic researchers and investors who wish to continue with the quest to construct simple but effective stock screens that not only beat the market but that also serve to separate winners from losers.

This research has provided evidence to shareholders, company executives, analysists and investors on which of the F-score's nine signals were most relevant in separating winners from losers on the JSE for the period 31 December 2004 to 31 October 2017. Shareholders and company executives should take note of the relevant signals for further attention in case they are not being effectively managed while analysts and investors are provided with a shortlist of signals that can be easily calculated from publically available information.

7.3 Limitations of the Research

While the study was designed as a causal study there are many factors that may influence the dependent variable. Therefore, as expressed by van der Merwe (2012, p. 40) the study should be viewed as a predictive study rather than one that can determine cause and effect with absolute certainty.

Transaction costs have not been accounted for in the quarterly rebalancing of portfolios and therefore the actual portfolio returns would have been lower than those detailed in this research. The inclusion of transaction costs may also have influenced the optimal holding and formation periods (Viljoen, 2016, p. 41).

The research spans a period during which South African listed companies converted their financial reporting standards from GAAP to IFRS. This conversion may have led to changes in financial reporting which could have an impact on the calculation of the F-score. This research will not investigate the impact of the conversion to IFRS and will assume the impact to be negligible as all companies within the sample were, by the nature of their listing on the JSE, required to convert to IFRS within similar periods.

A further limitation of the study stems from Broad Based Black Economic Empowerment (BBBEE) legislation that has required companies to transform their ownership structures. The different manner, degree to which, and timeframe over which companies have implemented the legislation would have resulted in different outcomes to the scoring of the EQ_OFFER signal. While an increase in the number of common shares in issue was considered a negative signal by Piotroski (2000), it could possibly be considered as a positive signal the context of BBBEE legislation and the varied financial and non-financial benefits that could accrue to a company.

As in the case of Shapiro (2016, p. 36), portfolios were constructed using an equal weighting. The use of a weighting based on market capitalisation may have produced different results.

This study was specifically designed to test the validity of the F-score's signals on the JSE and all analyses were conducted in the context of such. A similar study in the context of a market with different characteristics may well have delivered different results. Therefore, the interpretation and application of the results are restricted to the JSE and specifically to the timeframe over which the research was conducted.

7.4 Suggestions for Future Research

While the research did construct both a binary and ranked scale F-score, the purpose of the research was not to compare the predictive abilities of the two methods. It is therefore proposed that further research be conducted on both methods, across different sample periods and in different markets to assess whether the ranked scale F-score is more effective in separating winners from losers than its binary counterpart.

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Appendix 1. Additional Results for Section 5.1

Exception report – 31 December 2004

Style	Code	Tag	Date	ShortName	Detail	
Piotroski	ABL	LeverageTrend[]	31 Dec 2004	Abil	LI16	Total Serviced Debt
Piotroski	ABT	ROA[]	31 Dec 2004	Ambit	IS18	Profit After Tax (as published)
Piotroski	ACH	ROA[]	31 Dec 2004	Arch	IS18	Profit After Tax (as published)
Piotroski	ACP	RoaTrend[]	31 Dec 2004	Acucap	AS18,-2	
Piotroski	ADI	ROA[]	31 Dec 2004	AdaptIT	IS18	Profit After Tax (as published)
Piotroski	ADO	ROA[]	31 Dec 2004	Adonis	IS18	Profit After Tax (as published)
Piotroski	AEC	ROA[]	31 Dec 2004	Anbeeco	IS18	Profit After Tax (as published)
Piotroski	AEN	ROA[]	31 Dec 2004	Altron Pref	IS18	Profit After Tax (as published)
Piotroski	AFB	ROA[]	31 Dec 2004	Alexfbs	IS18	Profit After Tax (as published)
Piotroski	AFG	ROA[]	31 Dec 2004	Afgem	IS18	Profit After Tax (as published)
Piotroski	AFI	ROA[]	31 Dec 2004	Aflife	IS18	Profit After Tax (as published)
Piotroski	AFL	ROA[]	31 Dec 2004	Afrikander Lease	IS18	Profit After Tax (as published)
Piotroski	AHH	ROA[]	31 Dec 2004	Ahealth	IS18	Profit After Tax (as published)
Piotroski	ALD	ROA[]	31 Dec 2004	Aludie	IS18	Profit After Tax (as published)
Piotroski	ANA	ROA[]	31 Dec 2004	Adrenna	IS18	Profit After Tax (as published)
Piotroski	AND	ROA[]	31 Dec 2004	Andulela	IS18	Profit After Tax (as published)
Piotroski	AON	ROA[]	31 Dec 2004	Af & Over-N-	IS18	Profit After Tax (as published)
Piotroski	APA	ROA[]	31 Dec 2004	ApexHi-A	IS18	Profit After Tax (as published)
Piotroski	APB	ROA[]	31 Dec 2004	ApexHi-B	IS18	Profit After Tax (as published)

Piotroski	APE	ROA[]	31 Dec 2004	Aps-Tech	IS18	Profit After Tax (as published)
Piotroski	AQL	ROA[]	31 Dec 2004	Aquila	IS18	Profit After Tax (as published)
Piotroski	AQP	MarketCap[]	31 Dec 2004	Aquarius		
Piotroski	ARD	ROA[]	31 Dec 2004	Ardor	IS18	Profit After Tax (as published)
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	ASG	ROA[]	31 Dec 2004	AssMang	IS18	Profit After Tax (as published)
Piotroski	AVI	ROA[]	31 Dec 2004	AVI	AS18,-1	
Piotroski	AVU	ROA[]	31 Dec 2004	Avusa	IS18	Profit After Tax (as published)
Piotroski	AWT	MarginTrend[]	31 Dec 2004	Awethu	IS01,-1	
Piotroski	BAT	LeverageTrend[]	31 Dec 2004	Brait	LI16	Total Serviced Debt
Piotroski	BCX	RoaTrend[]	31 Dec 2004	Business Connexion	=[AS18,-2]	Prior(2):Total Assets
Piotroski	BDE	ROA[]	31 Dec 2004	Bidbee	IS18	Profit After Tax (as published)
Piotroski	BEE	RoaTrend[]	31 Dec 2004	Beget	AS18,-2	
Piotroski	BGA	ROA[]	31 Dec 2004	B-Africa	AS18,-1	
Piotroski	BRM	ROA[]	31 Dec 2004	Bearman	IS18	Profit After Tax (as published)
Piotroski	BRN	ROA[]	31 Dec 2004	Brimstone-N	AS18,-1	
Piotroski	BSB	ROA[]	31 Dec 2004	Busby	IS18	Profit After Tax (as published)
Piotroski	BTG	ROA[]	31 Dec 2004	BTG	IS18	Profit After Tax (as published)
Piotroski	CAE	MarginTrend[]	31 Dec 2004	Capemp	IS01	Turnover
Piotroski	CAP	MarginTrend[]	31 Dec 2004	Capemp	IS01	Turnover
Piotroski	CFR	ROA[]	31 Dec 2004	Richemont	IS18	Profit After Tax (as published)
Piotroski	CFX	ROA[]	31 Dec 2004	Conafex	IS18	Profit After Tax (as published)
Piotroski	CGN	ROA[]	31 Dec 2004	Cognition	IS18	Profit After Tax (as published)
Piotroski	CLO	RoaTrend[]	31 Dec 2004	Calulo	AS18,-2	
Piotroski	CML	RoaTrend[]	31 Dec 2004	Coronation	AS18,-2	
Piotroski	CNC	ROA[]	31 Dec 2004	Concor	IS18	Profit After Tax (as published)
Piotroski	CND	ROA[]	31 Dec 2004	Conduit	IS18	Profit After Tax (as published)
Piotroski	CNX	ROA[]	31 Dec 2004	Conafex	IS18	Profit After Tax (as published)
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	CPC	ROA[]	31 Dec 2004	Corpcap	AS18,-1	
Piotroski	CPI	LeverageTrend[]	31 Dec 2004	Capitec	LI16	Total Serviced Debt

Piotroski	CPT	ROA[]	31 Dec 2004	Captall	IS18	Profit After Tax (as published)
Piotroski	CRW	MarginTrend[]	31 Dec 2004	Corwil	IS01	Turnover
Piotroski	CVI	MarginTrend[]	31 Dec 2004	Capevin	IS01	Turnover
Piotroski	CVS	ROA[]	31 Dec 2004	Corvus	IS18	Profit After Tax (as published)
Piotroski	DMR	ROA[]	31 Dec 2004	Diamcor	IS18	Profit After Tax (as published)
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	ECO	ROA[]	31 Dec 2004	Edcon	IS18	Profit After Tax (as published)
Piotroski	ECS	RoaTrend[]	31 Dec 2004	Ecsponent	AS18,-2	
Piotroski	ELH	ROA[]	31 Dec 2004	Ellerines	IS18	Profit After Tax (as published)
Piotroski	ELX	ROA[]	31 Dec 2004	Elexir	AS18,-1	
Piotroski	EMI	ROA[]	31 Dec 2004	Emira	IS18	Profit After Tax (as published)
Piotroski	EMN	ROA[]	31 Dec 2004	E Media	IS18	Profit After Tax (as published)
Piotroski	ENV	ROA[]	31 Dec 2004	Enserv	IS18	Profit After Tax (as published)
Piotroski	EUR	ROA[]	31 Dec 2004	Eureka	IS18	Profit After Tax (as published)
Piotroski	FSR	LeverageTrend[]	31 Dec 2004	Firstrand	LI16	Total Serviced Debt
Piotroski	GDO	MarginTrend[]	31 Dec 2004	GoldOne	IS01	Turnover
Piotroski	GGM	ROA[]	31 Dec 2004	Goliath	IS18	Profit After Tax (as published)
Piotroski	GLL	ROA[]	31 Dec 2004	Glovil	IS18	Profit After Tax (as published)
Piotroski	GMF	MarginTrend[]	31 Dec 2004	Gencor	IS01	Turnover
Piotroski	GNK	ROA[]	31 Dec 2004	Grintek	IS18	Profit After Tax (as published)
Piotroski	HAL	ROA[]	31 Dec 2004	Halogen	IS18	Profit After Tax (as published)
Piotroski	HCL	ROA[]	31 Dec 2004	Hercol	IS18	Profit After Tax (as published)
Piotroski	HWA	ROA[]	31 Dec 2004	Hwange	AS18,-1	
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	ICC	RoaTrend[]	31 Dec 2004	ICC	AS18,-2	
Piotroski	ICT	ROA[]	31 Dec 2004	Incent	IS18	Profit After Tax (as published)
Piotroski	IFR	RoaTrend[]	31 Dec 2004	IFour Properties	AS18,-2	
Piotroski	ING	ROA[]	31 Dec 2004	Ingenuity	IS18	Profit After Tax (as published)
Piotroski	INL	LeverageTrend[]	31 Dec 2004	Investec	LI16	Total Serviced Debt
Piotroski	INP	ROA[]	31 Dec 2004	Investec Plc	IS18	Profit After Tax (as published)

Piotroski	INS	ROA[]	31 Dec 2004	INSURE	IS18	Profit After Tax (as published)
Piotroski	ITG	ROA[]	31 Dec 2004	Integrear	IS18	Profit After Tax (as published)
Piotroski	JNC	ROA[]	31 Dec 2004	Johnnic	IS18	Profit After Tax (as published)
Piotroski	KAP	ROA[]	31 Dec 2004	KAP	AS18,-1	
Piotroski	KLG	ROA[]	31 Dec 2004	Kelgran	IS18	Profit After Tax (as published)
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	KMB	ROA[]	31 Dec 2004	Kumba	IS18	Profit After Tax (as published)
Piotroski	LAN	ROA[]	31 Dec 2004	LA Group -N-	IS18	Profit After Tax (as published)
Piotroski	LBH	LeverageTrend[]	31 Dec 2004	Liberty	LI16	Total Serviced Debt
Piotroski	LEW	ROA[]	31 Dec 2004	Lewis	AS18,-1	
Piotroski	MAF	ROA[]	31 Dec 2004	M & F	IS18	Profit After Tax (as published)
Piotroski	MCP	ROA[]	31 Dec 2004	Miccprop	IS18	Profit After Tax (as published)
Piotroski	MCU	MarginTrend[]	31 Dec 2004	mCubed	IS01,-1	
Piotroski	MES	MarginTrend[]	31 Dec 2004	Messina	IS01,-1	
Piotroski	MIP	ROA[]	31 Dec 2004	Merchant	IS18	Profit After Tax (as published)
Piotroski	MMI	ROA[]	31 Dec 2004	MMI Holdings	AS18,-1	
Piotroski	MOR	ROA[]	31 Dec 2004	Morvest	IS18	Profit After Tax (as published)
Piotroski	MOZ	ROA[]	31 Dec 2004	Metoz	IS18	Profit After Tax (as published)
Piotroski	MRI	ROA[]	31 Dec 2004	MineResInv	IS18	Profit After Tax (as published)
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	MRN	ROA[]	31 Dec 2004	Marshalls-N	IS18	Profit After Tax (as published)
Piotroski	MTL	LeverageTrend[]	31 Dec 2004	Mercantile	LI16	Total Serviced Debt
Piotroski	MVL	MarginTrend[]	31 Dec 2004	Mvela	IS01	Turnover
Piotroski	NAN	RoaTrend[]	31 Dec 2004	Nail -N-	AS18,-2	
Piotroski	NBC	ROA[]	31 Dec 2004	NewBond	IS18	Profit After Tax (as published)
Piotroski	NED	LeverageTrend[]	31 Dec 2004	Nedbank	LI16	Total Serviced Debt
Piotroski	NMS	ROA[]	31 Dec 2004	Namsea	IS18	Profit After Tax (as published)
Piotroski	OML	LeverageTrend[]	31 Dec 2004	Old Mutual	LI16	Total Serviced Debt
Piotroski	OMN	ROA[]	31 Dec 2004	Omnia	IS18	Profit After Tax (as published)
Piotroski	ORE	RoaTrend[]	31 Dec 2004	Orion	AS18,-2	
Piotroski	PAL	ROA[]	31 Dec 2004	Pals	IS18	Profit After Tax (as published)

Piotroski	PBT	ROA[]	31 Dec 2004	PBT	IS18	Profit After Tax (as published)
Piotroski	PET	RoaTrend[]	31 Dec 2004	Petmin	AS18,-2	
Piotroski	PMA	ROA[]	31 Dec 2004	Primedia	IS18	Profit After Tax (as published)
Piotroski	PMN	ROA[]	31 Dec 2004	Primedia N	IS18	Profit After Tax (as published)
Piotroski	PPE	EfficiencyTrend[]	31 Dec 2004	Purple Capital	< -5	
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	PRO	ROA[]	31 Dec 2004	Proper	IS18	Profit After Tax (as published)
Piotroski	PSC	ROA[]	31 Dec 2004	Pasdec	IS18	Profit After Tax (as published)
Piotroski	PSG	RoaTrend[]	31 Dec 2004	PSGI	AS18,-2	
Piotroski	PTC	Accrual[]	31 Dec 2004	Putco	CD09	Net Cash Generated
Piotroski	PTG	ROA[]	31 Dec 2004	Peermont	IS18	Profit After Tax (as published)
Piotroski	PWK	MarginTrend[]	31 Dec 2004	Pikwik	IS01	Turnover
Piotroski	RAH	MarginTrend[]	31 Dec 2004	Ra-Hold	IS01,-1	
Piotroski	RES	ROA[]	31 Dec 2004	Resilient	AS18,-1	
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	RLY	ROA[]	31 Dec 2004	Relyant	IS18	Profit After Tax (as published)
Piotroski	RMH	MarginTrend[]	31 Dec 2004	RMBH	IS01	Turnover
Piotroski	RNG	MarginTrend[]	31 Dec 2004	Randgold	IS01	Turnover
Piotroski	SBK	LeverageTrend[]	31 Dec 2004	Stanbank	LI16	Total Serviced Debt
Piotroski	SCP	ROA[]	31 Dec 2004	Stellar	IS18	Profit After Tax (as published)
Piotroski	SFN	LeverageTrend[]	31 Dec 2004	Sasfin	LI16	Total Serviced Debt
Piotroski	SGG	ROA[]	31 Dec 2004	Sage	IS18	Profit After Tax (as published)
Piotroski	SLM	LeverageTrend[]	31 Dec 2004	Sanlam	LI16	Total Serviced Debt
Piotroski	SLO	RoaTrend[]	31 Dec 2004	Selco	AS18,-2	
Piotroski	SNG	ROA[]	31 Dec 2004	Synergy	IS18	Profit After Tax (as published)
Piotroski	SNT	RoaTrend[]	31 Dec 2004	Santam	AS18,-2	
Piotroski	SNV	RoaTrend[]	31 Dec 2004	Santova	AS18,-2	
Piotroski	SRL	ROA[]	31 Dec 2004	SA Retail	IS18	Profit After Tax (as published)
Piotroski	STI	ROA[]	31 Dec 2004	Stilfontein	IS18	Profit After Tax (as published)
Piotroski	SVN	ROA[]	31 Dec 2004	Sabvest -N-	IS18	Profit After Tax (as published)
Piotroski	TIW	ROA[]	31 Dec 2004	Tiwheel	IS18	Profit After Tax (as published)
Piotroski	TMT	MarginTrend[]	31 Dec 2004	Trematon	IS01	Turnover

Piotroski	TPN	ROA[]	31 Dec 2004	Corpcap	IS18	Profit After Tax (as published)
Piotroski	TRT	ROA[]	31 Dec 2004	Tourvest	IS18	Profit After Tax (as published)
Piotroski	UBU	ROA[]	31 Dec 2004	Ububele	IS18	Profit After Tax (as published)
Piotroski	UTR	ROA[]	31 Dec 2004	Unitrans	IS18	Profit After Tax (as published)
Piotroski	VIL	MarginTrend[]	31 Dec 2004	Village	IS01	Turnover
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	VKE	ROA[]	31 Dec 2004	Vukile	IS18	Profit After Tax (as published)
Piotroski	VOX	ROA[]	31 Dec 2004	Voxtelecom	IS18	Profit After Tax (as published)
Style	Code	Tag	Date	ShortName	Detail	
Piotroski	VTL	ROA[]	31 Dec 2004	Ventel	IS18	Profit After Tax (as published)
Piotroski	WBH	ROA[]	31 Dec 2004	W B Hold	IS18	Profit After Tax (as published)
Piotroski	WES	MarginTrend[]	31 Dec 2004	Wesco	IS01	Turnover
Piotroski	WLN	ROA[]	31 Dec 2004	Wooltru -N-	IS18	Profit After Tax (as published)
Piotroski	YTH	ROA[]	31 Dec 2004	YTHRK	IS18	Profit After Tax (as published)

Appendix 2. Additional Results for Section 5.2

StyleEngine Ranked percentages for transformations

Characteristic	RankPct	Return
ROA[]	10%	17,5%
ROA[]	30%	14,0%
ROA[]	50%	15,1%
ROA[]	70%	15,0%
ROA[]	90%	9,1%
MarginTrend[]	10%	12,2%
MarginTrend[]	30%	14,7%
MarginTrend[]	50%	18,4%
MarginTrend[]	70%	13,1%
MarginTrend[]	90%	17,2%
Accrual[]	10%	13,2%
Accrual[]	30%	16,0%
Accrual[]	50%	14,4%
Accrual[]	70%	17,9%
Accrual[]	90%	12,6%
EfficiencyTrend[]	10%	13,1%
EfficiencyTrend[]	30%	13,9%
EfficiencyTrend[]	50%	16,7%
EfficiencyTrend[]	70%	17,7%
EfficiencyTrend[]	90%	11,2%

LiquidityTrend[]	**10%**	**14,1%**
LiquidityTrend[]	**30%**	**15,3%**
LiquidityTrend[]	**50%**	**15,6%**
LiquidityTrend[]	**70%**	**14,5%**
LiquidityTrend[]	**90%**	**13,3%**
Characteristic	**RankPct**	**Return**
LeverageTrend[]	**10%**	**12,8%**
LeverageTrend[]	**30%**	**16,4%**
LeverageTrend[]	**50%**	**15,2%**
LeverageTrend[]	**70%**	**10,2%**
LeverageTrend[]	**90%**	**14,2%**
CFO[]	**10%**	**16,6%**
CFO[]	**30%**	**16,3%**
CFO[]	**50%**	**15,0%**
CFO[]	**70%**	**15,2%**
CFO[]	**90%**	**7,8%**
RoaTrend[]	**10%**	**12,6%**
RoaTrend[]	**30%**	**16,6%**
RoaTrend[]	**50%**	**16,9%**
RoaTrend[]	**70%**	**16,5%**
RoaTrend[]	**90%**	**13,9%**
EquityIssueTrend[]	**10%**	**11,3%**
EquityIssueTrend[]	**30%**	**11,7%**
EquityIssueTrend[]	**50%**	**11,9%**
EquityIssueTrend[]	**70%**	**19,2%**
EquityIssueTrend[]	**90%**	**16,2%**

Appendix 3. Ethical Clearance

Gordon Institute of Business Science
University of Pretoria

27July 2017

Timothy Nast

Dear Timothy,

Please be advised that your application for Ethical Clearance has been approved.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards

GIBS MBA Research Ethical Clearance Committee

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